Co-Located Multimodal Sensing: A Next Generation Solution for Wearable Health

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***Abstract*— A novel physiological sensor which combines electrical and mechanical modalities is introduced. The electrical component behaves as a standard electrode and detects changes in bioelectrical potential, whereas the mechanical component comprises an electret condenser microphone with a thin and light diaphragm, making it sensitive to local mechanical activity but immune to global body movements. A key feature of the proposed sensor is that the microphone is positioned directly on top of the electrode component (co-location). In conjunction with co-located electromechanical sensing, the ability of the electrode to flex allows for motion to be detected at the same location where it corrupts the electrical physiological response. Thus, the output of the mechanical sensor can be used to reject motion-induced artifacts in physiological signals, offering improved recording quality in wearable health applications. We also show that the co-located electrical and mechanical modalities provide derived information beyond unimodal sensing, such as pulse arrival time and breathing, thus enhancing the utility of the proposed device and highlighting its potential as a diagnostic tool.**

***Index Terms*— Multimodal sensing, electrophysiology, electrocardiography, electroencephalography, biosensors, noise cancellation.**

I. Introduction

THE costs of healthcare are rapidly becoming a burden in many developed countries, taking up a significant proportion of their GDPs. Technological advances are envisaged to play crucial role in reducing these costs, through e.g. continuous monitoring of chronic patients outside the clinic. The emergence of patient-centred healthcare, which includes out-of-clinic monitoring and diagnosis, is facilitated by the rapid miniaturisation of electronics and improvements in battery capacity, gradually making wearable health technologies a reality. Commercial non-clinical products for recording cardiac function (e.g. Basis) and even brain function (e.g. Emotiv, Mindo) are already available. Nevertheless, there are several obstacles to be overcome before wearable devices become reliable clinical tools; in particular there is scope for significant improvements at the sensor level.

Manuscript received April 9, 2014; revised June 24, 2014; accepted June 26, 2014. Date of publication July 10, 2014; date of current version November 5, 2014. The associate editor coordinating the review of this paper and approving it for publication was Dr. Ravinder S. Dahiya.

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Digital Object Identifier 10.1109/JSEN.2014.2338612

Physiological sensors employ different recording modalities. Typical examples are sensors for electrical potentials (electrodes); electrochemical sensors such as blood glucose, pH and ISFET sensors; optical sensors for oximetry or blood gas measurements; and accelerometers as well as other transducers, which record mechanical displacements. The diagnosis of a specific health condition often requires a specific recording modality. For instance, the electrocardiography (ECG) represents the gold standard for estimating heart rate variability (HRV), while mechanical observations from transducers or photoplethysmography (PPG) recordings are used to determine the pulse transit time (PTT). Furthermore, some physiological variables can only be determined by combining different sensor modalities, such as cardiac pulse arrival time (PAT).

Current electrode technologies are now established in many clinical settings, however, they are typically developed to obtain low electrical impedance between the instrumentation equipment and the body. In practice, one of the biggest challenges associated with physiological recordings are the motion artefacts induced by relative movements between the electrode and the skin, which affect the electro-chemical electrode-skin interface, thus causing interference. Despite a significant effort to develop mechanically stable electrode-skin interfaces, current electrodes are still prone to motion artefacts as well as other skin-related effects [1], [2] (e.g. skin stretch). Research in electrode technology has primarily focused on enabling physiological recordings without the conductive gel; while this provides greater user comfort, it typically increases the level of signal degradation due to motion artefacts. Even in controlled environments where movements of a subject are constrained, modern electrodes frequently provide suboptimal signal quality. This is particularly detrimental when dealing with vulnerable populations [3] such as the elderly and those suffering from neurodegenerative diseases (e.g. Parkinson's disease).

While both electrodes and mechanical sensors (e.g. PPG) suffer from skin-contact movement, such motion artefacts may not be a disadvantage if the inferences from sensors of different modalities are combined to identify and reject the artefact. Early work by Hamilton *et al.* [2], [4] investigated how to augment standard electrodes in recording ECG with stretch and optical sensors which measure movement nearby the electrodes. The estimates of the artefacts were then computed using signal processing and subtracted from corrupted ECG to obtain the clean/desired signal. Similarly, Devlin *et al.* [5] and more recently Kim *et al.* [6] used electrode-skin impedance measurements as a means of motion artefact rejection. Other

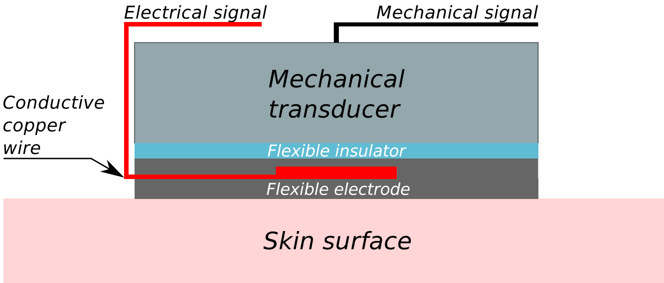

Fig. 1. Concept of the multimodal sensor which measures electrical and mechanical responses from the same location on the body (co-location).

approaches used magneto-resistive sensors [7], accelerometers [8], pressure sensors [9] and combinations of these [10] as well as electrode-skin half-cell potential monitoring [11]. Far less multimodal research has been conducted in the area of artefact removal for electroencephalography (EEG), yet this is much more challenging as the EEG potentials are extremely weak (tens of microvolts) [12] and are often much smaller than the motion potentials. A recent study used a tri-axial accelerometer placed on the electrode cap to reduce motion artefacts caused by head movements [3].

All this highlights the need for multimodal sensors that combine electrical and mechanical physiological activity to perform sensor-level fusion for multi-feature diagnosis and to enable greater robustness in wearable scenarios. In mechanical sensing, it is desirable that only the activity with respect to the skin surface be detected, i.e. the body of the subject must act as a frame of reference – *local sensing*. This is clearly not the case when using e.g. an accelerometer as it detects global body movements as well as local ones, its output therefore contains additional components not related to movement artefacts. Additionally, we emphasise the importance of *co-located sensing*, where both modalities are recorded from exactly the same location. This promises critical advantages in artefact rejection scenarios as, otherwise, the artefact may not be present within all modalities.

To this end, we propose to combine an electrode with a mechanical transducer to obtain a robust and reliable signal acquisition unit that satisfies both *local* and *co-located* criteria, as shown in Figure 1. Here, the transducer is mounted directly on top of the electrode, hence both elements are co-located and integrated inside a single miniature package. The mechanical transducer is chosen so as to be sensitive only to the local electrode movements and has the body surface of a subject as a frame of reference. Both modalities of the combined sensor operate concurrently, so that motion-induced artefacts are captured by the transducer directly *through* the electrode, thus ensuring high sensitivity and accuracy of motion artefact estimation via the mechanical component.

We also show that the capabilities of the proposed co-located sensor extend beyond the denoising of the electrical output as it provides means of recording a wide range of mechanical biosignals, e.g. arterial/venous pulsation, respiration; these are obtained either separately or in conjunction with the electrical activity. The separate modalities of the proposed sensor are also shown to provide additional bio-

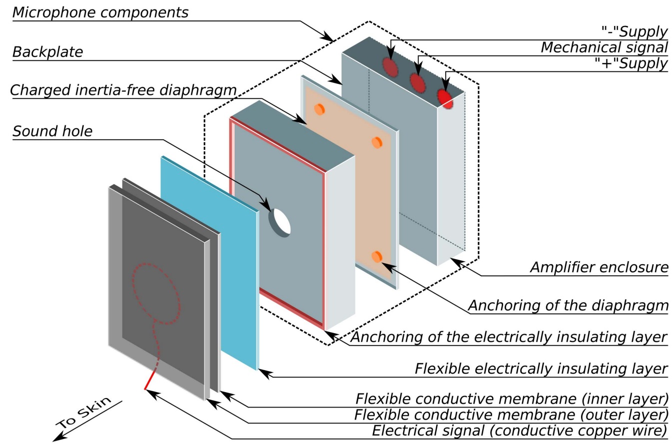

Fig. 2. Detailed construction of the multimodal sensor.

medical parameters like PAT, which is valuable in estimating blood pressure variability. In summary, the proposed device replaces several individual sensors at no loss in sensitivity, thus reducing clutter and lending itself to applications in emerging wearable sensing systems.

II. Multimodal Physiological Sensor

The proposed sensor is a single device that records two modalities from the same body location. This is achieved through augmentation of the electrode with a miniature electret condenser microphone (ECM). For the prototype, we have chosen a 9723 GX model from Sonion, primarily developed for hearing aids applications, it has a high baseline sensitivity of $-33\,\mathrm{dBV/Pa}$ at $1\,\mathrm{kHz}$, a very low current consumption of only $35\,\mu\mathrm{A}$ and low frequency cut-off at $20\,\mathrm{Hz}$. From a mechanical-motion point of view the cut-off at $20\,\mathrm{Hz}$ is relatively high and preferably should be even lower, but it is a design feature of the electret microphone and is one of the lowest in its class.

A. Construction of the Multimodal Sensor

The proposed sensor yields a reliable estimate of the motion artefact by sensing the mechanical displacement through the electrode mounted directly on top of the sound hole on the front face of the microphone, as shown in Figure 2.

The microphone, that provides the mechanical modality of the sensor, is an active electret condenser type and comprises two capacitor plates. One of the plates is formed by a thin and light (low inertia) diaphragm on which the charge is deposited during manufacturing. The backplate consists of a rigid piece of metal connected to the microphone casing. Compression waves pass through the hole on the front face of the casing and the geometry of the hole determines, in part, the frequency response of the microphone. The waves arriving at the microphone cause the diaphragm movement, leading to changes in distance between the capacitor plates. Such changes in capacitance produce changes in the potential difference between the plates which is then amplified, hence three connections on the microphone: positive supply, negative

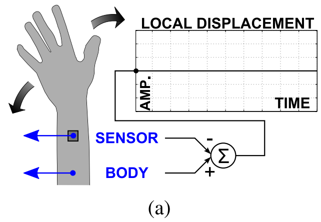

Fig. 3. Principle of multimodal sensor. (a) The diaphragm inside the mechanical transducer has very small mass, thus body movements which do not cause displacements of the electrode with respect to skin are not detected. (b) Abrupt movements leading to displacements of the sensor with respect to the skin are detected by the mechanical transducer directly through the surface; such a mechanical signal can be used to denoise the electrical signal.

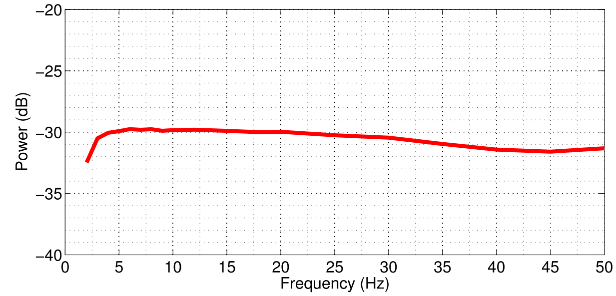

Fig. 4. Frequency response of the mechanical part of the multimodal sensor. The sensor was firmly attached to the vibration plate oscillating at a 1 mm displacement amplitude and the frequency was varied over a 2 – 50 Hz range.

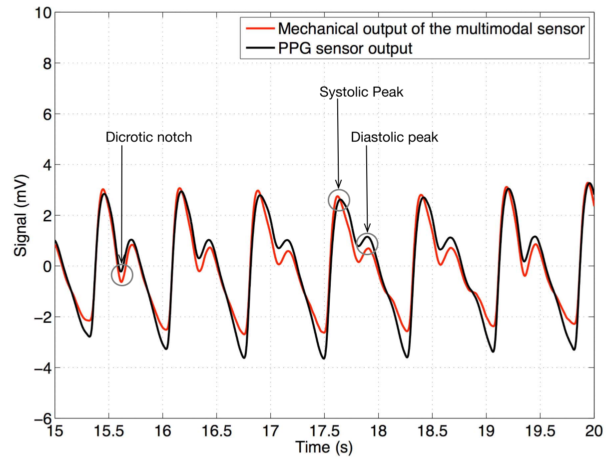

Fig. 5. An overlay plot of the mechanical output of the multimodal sensor and the output of a PPG sensor. Both signals were filtered to the 1 – 30 Hz range and the PPG signal was scaled to the same amplitude range as the transducer signal.

supply and signal. The negative supply contact is connected to the casing of the microphone which, in turn, is connected to the backplate of the capacitor. Hence, although the casing is conductive and therefore capable of detecting electrical activity, it cannot be used as an electrode.

The electrical modality of the sensor is obtained by first sealing the microphone with several layers of thin flexible insulating material, ensuring that there is a pocket of air formed above the sound hole. Subsequently, a layer of flexible conductive material is applied, followed by an attachment of a thin wire. In the last step, several more layers of a flexible conductor are deposited on top of the wire.

The flexibility of the electrode ensures that compression waves caused by skin movement propagate freely into the sound hole, where they are detected by the microphone. Other forms of mechanical excitation directly beneath the electrode can also be sensed. The diaphragm in the microphone has very small mass (and therefore negligible inertia), so that it is sensitive only to local mechanical activity and to a large extent immune to whole or global body movements, as depicted in Figure 3.

B. Sensor Characterisation

The electrically sensitive part of the proposed device was found to have similar impedance characteristics to those of standard electrodes used for biosignal acquisition. It has also shown good resistance to wear and tear as well as negligible impedance degradation after a month of regular usage (several times a week).

The mechanical part of the sensor was characterised through a number of tests designed to investigate its linearity and sensitivity over frequency. The device was placed on a vibration plate (VP) to obtain an estimate of its frequency response in a scenario comparable to motion-induced displacements along the sensor/skin interface. The electrically conductive face of the sensor that is attached to the skin (see Figure 2) was fixed to the VP with a strong double-sided adhesive tape and also covered with several layers of medical tape. Such an arrangement is a good model of a sensor placed over a pulsating region on the human body, e.g. at the radial artery site. The displacement of the plate was set to 1 mm and the frequency was varied over a 2 – 50 Hz range. These settings formed a reasonable compromise allowing us to characterise the sensor over the majority of the frequencies of interest in typical electrophysiological recordings, without introducing undesirable artefacts not related to sensor characteristics.

Figure 4 shows the transfer function based on the mechanical output of the sensor. Observe that in the experimental frequency range the mechanical response of the sensor remained within a 3 dB window, exhibiting good linearity in the amplitude characteristic across frequency. As discussed earlier, the microphone has low frequency cut-off at around 20 Hz and based on information provided by Sonion, different units of the same model have different roll-off rates at below that frequency. This implies that the microphone is expected to act as a differentiator for very low frequency acoustic signals (non-linear amplitude characteristic of the frequency response). The likely reason for the observed linearity in Figure 4 is that the characteristics of the microphone have been modified by sealing its front face with a flexible membrane, thereby creating an insulated pocket of air between the electrode and the diaphragm inside the device. Consequently, any movement (perpendicular to the skin) of the conductive membrane causes changes in pressure inside that pocket of air, which in turn leads to a corresponding movement of the diaphragm. Motion of the diaphragm is coupled to the motion of the membrane, thus enabling the key feature of the proposed device – its high sensitivity to mechanical displacements of the flexible electrode.

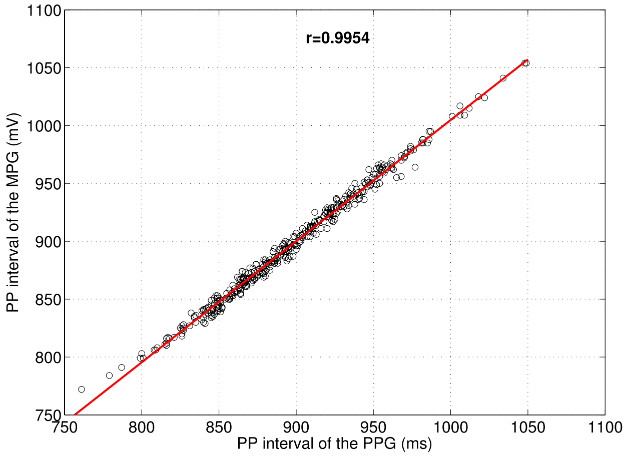

Fig. 6. The Pearson correlation coefficient between PPG-derived and MPG-derived PP intervals for a healthy male subject of age 27.

The linear response to the displacement of the electrode membrane was next verified in the considered frequency range for a real world physiological scenario, whereby the device was placed inside a finger clip next to the phototransistor of the photoplethysmography sensor HRM-2511E by Kyoto Electronics Co. Figure 5 shows the mechanical output of the sensor (MPG) together with the PPG waveform. Observe that the photo- and mechanical- plethysmography waveforms are highly correlated, confirming that the microphone within the multimodal sensor is capable of producing a good proxy of the PPG waveform. The sensitivity of the ECM is high enough to replicate even minute details of the PPG signal, such as the dicrotic notch; the time difference between the systolic and the diastolic peaks can be readily measured as well. To further illustrate the good correspondence between the standard PPG and the MPG, we have evaluated the Pearson correlation coefficient between beat-to-beat changes of the peak-to-peak interval (PPI) derived from photo- and mechanical- plethysmography waveforms from a healthy subject. Figure 6 demonstrates a high correlation between the estimates from a 300 s recording (correlation coefficient 0.9954).

III. Enhanced Recording Quality

The modification of skin impedance and its half-cell potential in response to mechanical, electrical or thermal stimulation is well established, first observed in the 1920's and investigated by numerous authors since (see [1], [13]). The skin potential differs from that of the body interior, on average, by -15 mV on the forearm, and in general can vary between 10 mV and -70 mV [1]. There is a consensus that mechanical stimulation of the skin (e.g. stretching) can induce changes in its impedance and half-cell potential, thus interfering with other electrophysiological measurements. On repeated stimulation, and in the absence of sufficient relaxation time, the magnitude of the skin response to mechanical stimulation progressively decreases; the response to mechanical stimulation also decreases if the skin is abraded. The above-mentioned effects are the primary cause of motion artefacts in non-polarisable electrodes (e.g. *Ag/AgCl*) [14]. On the other hand, dry electrodes, being metallic (e.g. flexible electrode in the proposed sensor), form a capacitive interface, and thus have an additional half-cell potential established between the electrode surface and the skin. In such scenarios the primary cause of motion artefacts is the change in dimensions of the contact interface and relative movement of the electrode and the skin.

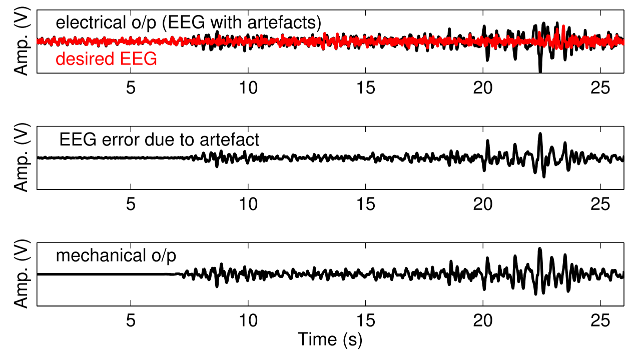

Fig. 7. Motion artefact detection. Top panel: the EEG signal corrupted with motion artefact together with the clean EEG obtained by averaging the signals from four standard electrodes. Middle panel: the difference between the noisy and clean EEG signal. Lower panel: the mechanical output of the multimodal sensor.

In particular, these phenomena represent a significant problem in EEG applications where the signal of interest is typically much weaker than the motion-induced artefacts. The conventional way of dealing with such artefacts is to detect their onset and subsequently discard the contaminated part of the recording. This reduces the size of the datasets and introduces discontinuities, leading to loss of information. In addition, if the motion artefacts do not have large amplitudes, it can be difficult to distinguish the underlying EEG, which leads to incorrect analysis. Advanced signal processing solutions can be used to identify and reject artefacts, e.g. based on independent component analysis [15]. Although extensions of such approaches exist for single channel analysis [16], they perform optimally in multi-channel scenarios.

A. Motion Artefact Rejection

To evaluate the ability of the proposed sensor to detect motion-induced artefacts in EEG signals, the multimodal sensor was attached to the middle of a subject's forehead using medical tape. Four standard electrodes were placed at a distance of 3 cm from the sensor and equidistant from each other. The average of the signals from these electrodes establishes the ground truth, i.e. the clean/desired EEG signal. All of the five electrical signals were measured with respect to the standard reference electrode placed on the right earlobe. The microphone component of the sensor was powered with a Duracell CR2032 coin cell. The g.tec g.USBamp unit was used for data acquisition of all the signals (five electrical and one mechanical) at a sampling frequency of 256 Hz. All the electrodes, including the electrode component of the multimodal sensor, were gelled with standard EEG electrolyte and the skin on the forehead was abraded.

The recordings were of approximately 45 s duration. The first 7 s were artefact free, subsequently the multimodal sensor

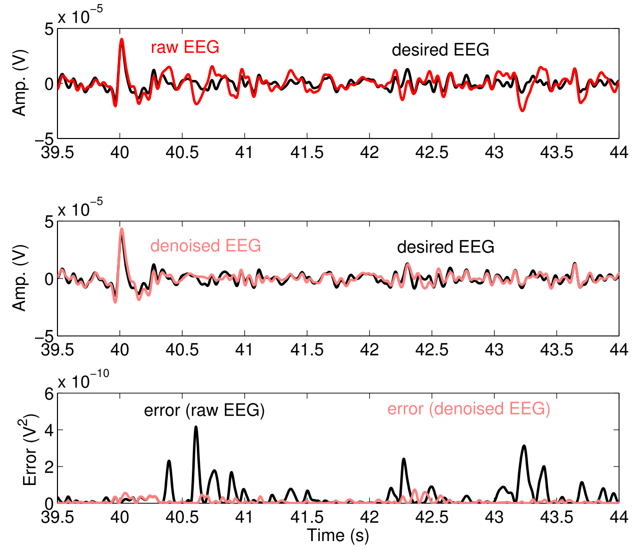

Fig. 8. Motion artefact removal. Top panel: clean/desired and corrupted EEG signals. Middle panel: desired and denoised EEG signals. Lower panel: the squared error prior to and after denoising.

was lightly pressed and rubbed in different directions with a finger, monotonically as well as abruptly, simulating the motion-induced artefact. The resultant signals from one of the experiments, filtered to 1 – 40 Hz range, are shown in Figure 7. The middle and the lower panels illustrate that the EEG error signal and the mechanical output of the sensor are highly correlated, verifying that the mechanical modality of the sensor is an accurate proxy of the motion-induced artefact and can be used to denoise the electrical output.

A tool based on multivariate empirical mode decomposition (MEMD), see [17] for more details, was applied to perform motion artefact rejection of the electrical signal (EEG) based on the mechanical signal. Figure 8 shows approximately 5 s of data; observe that the denoised waveform very closely follows the true EEG signal. The proposed sensor therefore enables high quality continuous EEG recordings in natural environments. Note that the considered scenario is particularly challenging, because the motion-induced artefact produces disturbances of approximately the same amplitude as the EEG signal itself, proving that the microphone is easily capable of detecting even the slightest displacements of the electrode.

IV. Multimodal Diagnosis

By definition, the electrical modality of the proposed sensor requires an additional sensor or electrode placed at a suitable distance to determine electrical potential. An advantage of mechanical sensing is that only a single sensor is required. For instance, in the study of electrical cardiac function, at least two electrodes must be placed on either side of the heart while a single PPG sensor placed on e.g. the fingertip, earlobe or radial artery site is sufficient. In applications within constrained spaces, e.g. inside the ear [18], [19], the mechanical modality of the sensor can be used independently to provide mechanical measurements, without the need for a reference sensor. On the other hand in instances where both modalities are accessible, they can be combined to improve the reliability and accuracy of the physiological readings, thereby enhancing the utility of the sensor as a diagnostic tool.

A. Cardiac Activity

New diagnostic insights can be gained by combining the recordings of electrical and mechanical attributes of cardiac function. At present, mechanical arterial/vein pulsations induced by cardiac activity are measured using PPG sensors based on modulations in skin-absorbed light. Pulse arrival time (PAT) – the lag between the R-peak in ECG and the systolic peak in PPG – can be used to assess the blood pressure variability [20], which in turn is related to the general health of the cardiovascular system. Also, the distance between adjacent PPG peaks is a good proxy for heart rate variability [21], and has direct usage in the diagnosis of stress, fatigue and other aspects of the autonomic cardiac function.

Most PPG sensors have relatively high power consumption, due to the high current drive demands of the light sources, making them unsuitable for wearable devices for continuous long-term recordings. A number of research groups working on bodily acoustic measurements have observed local pulsations with the aid of less power hungry microphones [22]. Nomura *et al.* [23] have investigated the pulsation waveforms at the radial artery site and have shown that a particular MEMS ECM supplemented with a cylindrical O-ring can sense the first derivative of the PPG signal.

We have found that the microphone embedded in the multimodal sensor readily detects local pulsations when placed on the wrist, neck, forehead, inside and behind the ear. This capability is enabled by the flexibility of the conductive material of the electrode and the insulating layer sealing the microphone, allowing pressure waves to travel from the blood vessels through the skin and the electrode into the microphone. Both the ECG and the MPG can be sensed from exactly the same location with the proposed sensor. Figure 9 shows both signals (electrical and mechanical) obtained from the radial artery site on the left wrist with the multimodal sensor where the electrical output is referenced to a standard electrode on the right wrist.[1]

B. Breathing

Breathing modulates the intensity (amplitudes) of both the electrical [24] and mechanical modalities of cardiac function [25]. During the inspiration phase the pressure inside the intrapleural cavity within which the heart resides, decreases, causing the right atrium to swell, increasing the stroke volume. The opposite phenomenon is observed during expiration, so the overall effect of the breathing is akin to a low frequency pump. Figure 10 illustrates that the amplitude-modulation phenomenon caused by respiration is observable within both the mechanical and the electrical outputs of the proposed sensor where, for reference, respiration effort estimated from a respiration belt is also plotted.

[1]Electrical measurements require an additional reference electrode (or reference multimodal sensor) placed some distance away from the sensor.

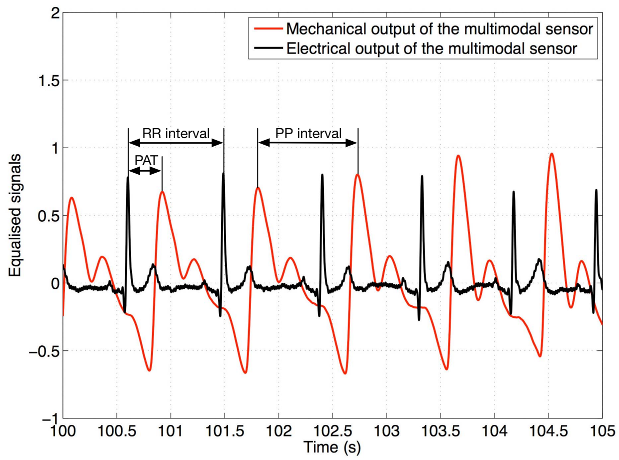

Fig. 9. HRV can be derived from the mechanical output of the sensor (single location), while PAT can be obtained by combining information from both modalities (requires another reference sensor/electrode). Both signals are obtained from a single multimodal sensor placed at the radial artery site.

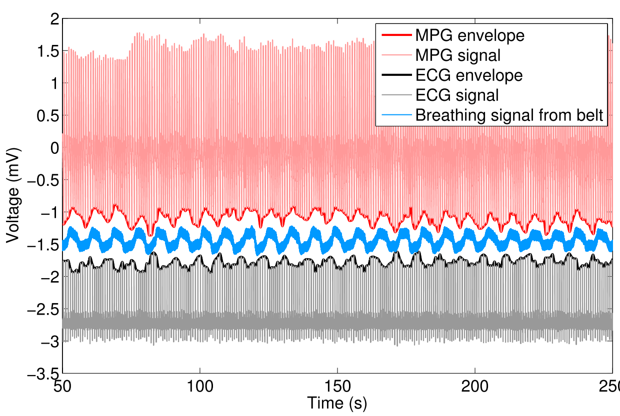

Fig. 10. The mechanical and electrical outputs of the multimodal sensor when placed at the radial artery site on the left wrist. The envelopes (amplitudes) of both signals closely follow the true breathing waveform obtained from a respiration belt.

In addition to amplitude, respiration also influences rate of the cardiac function; this is known as respiratory sinus arrhythmia (RSA). During the inspiration stage the heart rate increases, and decreases during expiration. By matching ventilation and perfusion, RSA benefits the efficiency of the gas exchange in the lungs [26]. Furthermore RSA magnitude has a number of clinical uses, primarily as a measure of cardiac vagal activity. It has been shown that autonomic dysregulation, in the form of reduced RSA, is associated with a variety of cardiovascular risk factors and, in particular, it is a significant predictor of hypertension, which in turn has a significant positive association with cardiac disease [27].

The peak-to-peak interval was calculated from both the mechanical (MPG) and electrical (ECG) modalities. Figure 11 shows the variations of each PPI in a fashion that is proportional to respiration effort estimated from a respiration belt. Figures 10 and 11 illustrate the modulation of amplitude and PPI information from both the mechanical and electrical modalities by respiration effort. When both modalities are available the sensor provides twice the number of samples provided by conventional single-modality approaches, hence enhancing the accuracy of the estimated RSA.

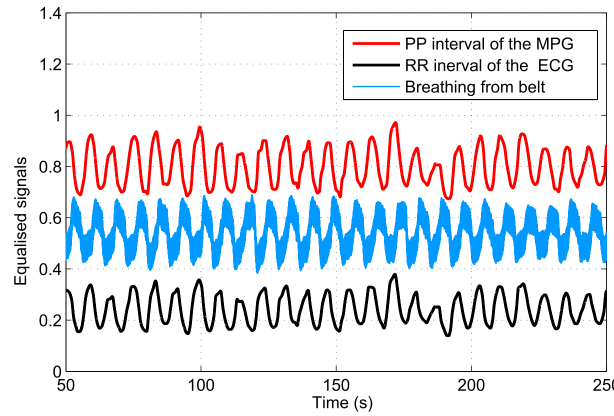

Fig. 11. The peak-to-peak interval (PPI) signals obtained from the mechanical and electrical outputs of the multimodal sensor when placed at the radial artery site on the left wrist. Observe that the PPI variations for each modality closely follow the true breathing waveform obtained from a respiration belt.

V. Conclusion

A novel multimodal physiological sensor has been developed for high efficiency electromechanical sensing. It consists of a mechanically flexible electrode placed on top of an electret condenser microphone. The construction of the sensor is such that the local mechanical disturbances below the sensor can be measured directly through the electrode surface with high accuracy and sensitivity. Owing to the co-location property of the sensor, the mechanical component is capable of detecting motion-induced artefacts and its output can be subsequently used to denoise the electrical component. This has been demonstrated experimentally, whereby motion artefact removal was performed for EEG recordings obtained by the sensor. The results have indicated that the proposed sensor promises improved recording quality of electrophysiological signals in wearable health applications. We have also demonstrated that the proposed device can be used to measure a range of biosignals, highlighting its appeal in multimodal diagnosis. For example, readings over the radial artery site enable simultaneous plethysmography and ECG acquisition. This allows for the derivation of additional parameters, such as PAT and HRV. Furthermore, the multimodal cardiac signatures can be combined to enhance measurement accuracy in the estimation of RSA.

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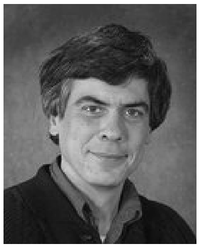

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