Commodity Sensors, Physiological Signals, Research Opportunities, and Practical Issues

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***Abstract*— We discuss selected emerging technologies in physiological signal processing, low-cost pervasive sensors, diagnostic pattern recognition, and some research issues they entail. Serious practical issues remain for signal acquisition from users in their own environments using these commodity sensors. To illustrate the technical issues, we describe a novel robust processing algorithm for mobile ECG sensors (i.e. non-contact capacitive sensors with low signal-to-noise ratios). We describe the detection techniques designed to function effectively with such noisy ECG data.**

***Keywords*— Biomedical signal processing, Biomedical transducers, Machine learning, Pattern recognition.**

I. Introduction

Several sensor types have become almost universally available and affordable to consumers in recent years. Concomitant cost reductions of microcontrollers allow low cost pervasive signal acquisition in many situations, spanning homes, workplaces, and clinical settings. There are numerous research efforts focused on finding medically relevant uses of signals from such pervasive sensors.

We provide an extended analysis of practical issues with electrocardiogram (ECG), photoplethysmogram (PPG), ballistocardiogram (BCG), and other processing under adverse conditions with commodity sensors, e.g. a non-contact capacitive sensor operating through clothing. We show that robust QRS-complex detection is prerequisite in the poor Signal-to-Noise Ratio (SNR) conditions typical of mobile and exercise applications. We contrast performance of earlier clinical grade algorithms, e.g. Pan-Tomkins [1], in poor SNR with our robust detection algorithms. This contrast could be illustrative of engineering developments needed to exploit commodity pervasive sensors in actual user environments.

II. Primary Sensors

The sensors discussed here are non-invasive, low-cost, widely available, hardware. Yet they are opening up a wide range of physiological signal processing, diagnostic research, and engineering opportunities. Moreover, the commodity cost levels open research and data collection to wider communities involved in developing medically relevant measurements.

A. *Electrocardiogram*

There are several types of cardiac sensors used to acquire signals, many claiming improved usability over the standard saline gel electrodes widely used in clinical settings, e.g.:

Dry electrodes - These do not require saline gel and are used to capture ECG signals [2]. Generally, these are stiff, can induce skin irritation in some subjects, and become uncomfortable for the wearer [3]. To capture a usable signal, these sensors may require the user to remain still during signal acquisition [4].

Capacitive non-contact electrodes – These sense signals across a gap between the sensors and the skin to capture signals with low SNR, depending on conditions [5]. These sensors can operate through hair, fabric, or the air, and may be placed on car seats, chairs, beds, etc. [6].

Piezoelectric sensors - may be used to "sense the in-ear pulse waves (EPW) and convert it to an electric current" [7]. The pulse waves may be interpreted with an algorithm to obtain heart rate. However, the heart rate measurements are affected by motion artifacts, which cause errors in the analytics. There are other types of piezoelectric sensors being used for heart-based analytics as well, sometimes in stretchable fabrics [8].

Conductive cloth - May be used as flexible capacitive electrodes but some sensors require pressure to ensure good skin contact [9]. Graphene oxide sensors may also be embedded in fabric [10].

Saline gel electrodes – These are the clinical gold-standard but must be secured to the skin, must be placed in exact locations on the body and must be used with wet conductive gel to obtain a good signal. These are the most commonly used sensors for clinical purposes [11]. They require the use of wet electrodes and may irritate the patient's skin [12].

Tattoos – These may be fabricated from very lightweight materials to measure ECGs, skin temperature, etc. and therefore offer greater comfort to the users [13].

Dry electrodes, capacitive devices such as conductive cloth, are much more comfortable for the patient/user because they do not require continuous contact enforced by a strap or adhesive [14]. This is particularly important for neonatal and burn patients who cannot tolerate the gel or pressure on the skin that saline gel electrodes require. Some vendors are using nanotechnology in fabrics [15] for continuous real time monitoring of cardiac signals. It is possible to use smart textiles as electrodes for ECG measurement purposes [16]. The benefit of the textile-based sensors is that the user does not have to wear uncomfortable chest straps or expensive watches. The fabrics are close to the skin, giving a good basis for acquiring cleaner signals. The fabric-based sensors do not need conductive gel, as traditional ECG sensors do.

For the purposes of clinical monitoring, the ECG devices should be low-energy and cost-effective. They should also require little patient interaction, should produce clean signals for analysis so that the QRS waves may be accurately detected and localized. The algorithms used should also be computationally efficient, particularly for mobile users[17]. Most of these sensors are designed to capture a single lead ECG called "rhythm strips" suitable to monitoring, but which do not provide the rich diagnostic detail of a traditional 12-lead ECG [18].

B. *Microphones*

Commodity microphones have long been available, e.g. Thomas Edison's 1887 patent application for the carbon button microphone [19], and Sessler and West's Electroacoustic Transducer patent on the electret microphone [20]. Both of these technologies became dominant for a time and remain in use today. Since then, many designs have become ubiquitous, e.g.: carbon button, condenser, dynamic, piezoelectric crystal, Electret, and lately MEMS, microphones. Applications include speech, heart sounds, auscultation of a variety of body sounds, and recently voice analysis for neurological and certain cardiac conditions.

C. *Accelerometers*

Accelerometers can provide relevant physiological measurements, with applications in medicine, rehabilitation, sports, and fitness. Accelerometers commonly used in smartphones are MEMS designs with at least three axis measurements-based capacitive sensing, and often nine axis with accelerometer, gyroscope, and magnetometer axes. There are many applications, e.g. Ballistocardiogram, gait analysis, athletic energy expenditure, heart rate, sleep tracking, step counting, and even Systolic Time Intervals [21], [22], [23], [24], [25].

D. *Photoplethysmograph (PPG)*

Photoplethysmography (PPG) optical sensors "measure blood perfusion through tissues by the emission of light rays" created by light-emitting diodes (LEDs). They are commonly found on fitness devices (e.g. FitBit) and also on calibrated pulse oximetry devices (often used in a hospital to capture pulse and respiration rates via a clamped device on an index finger). These sensors are cheap, uncomplicated to build, and do not require the use of gels or adhesives to capture the signals. The PPG signals may be analyzed to reveal pulse rate variability (PRV), pulse transit time through the cardiovascular system (for analysis of sleep-related symptoms), pulse wave velocity (to measure elasticity of the blood vessels) and other respiratory and cardiac health indicators [26].

PPG sensors may produce erroneous readings due to "characteristics such as skin tone, thickness of the fat layer and rigidity of the radial artery [27] If the PPG sensor is not tightly attached to the body (e.g., via a watch strap or finger clamp at appropriate pressures), the light diffuses and the data may be lost. Movement, especially during exercise) may also cause artifacts in the data. The finger clamp may also introduce artifacts by putting pressure on the fingertip, thus altering the blood perfusion characteristics.

Several types of PPG sensors are used to capture pulse rates and to measure pulse rate variability. They are also used to obtain continuous estimates of blood pressure [28].

III. DIAGNOSTIC SIGNALS

The primary sensors mentioned above capture raw time-series containing physiologically relevant signals, but detailed interpretations must be made in the context of the operation of the underlying generating systems.

A. *Electrocardiograms*

An ECG is a multichannel voltage time series of the electrical activity of the human heart. It is often recorded from electrodes adhered to the chest wall at prescribed positions using adhesive patches which hold saline gel for conductivity. Machine learning approaches, e.g. random forest classifiers, or Deep Neural Networks (DNNs), are often used with raw signals. But physiologically motivated feature extraction and interpretation requires detailed understanding of the anatomy and electrophysiology of the heart. For example: P-R interval and J-Wave offer little in the way of distinct frequency domain signatures, yet they are key diagnostics because of their critical time domain information on conductance and repolarization of the heart.

Heart rate variability (HRV) is defined as "the change in time intervals between adjacent heartbeats" in the ECG. Pulse rate variability (PRV) is measured via PPG sensors and is usually closely correlated with HRV when the subject is at rest. HRV is more clinically accurate than PRV in cases where the patient has frequent abnormal beats [29], such as premature ventricular contractions, ECG sensors should be used in those cases. Alterations in HRV are early indicators of fetal distress. Low HRV is a strong independent variable to predict both morbidity and mortality [30]. HRV may also be used to study and manage various neuropsychiatric disorders such as bipolar disorder [31].

Blood pressure variability (BPV), measured continuously, may be used to predict imminent cardiac events and is an indicator that the subject may suffer from obstructive sleep apnea, a serious chronic disease [32].

The advent of smaller sensors that draw less power allows development of continuous biomedical signal monitoring for two primary purposes: fitness monitoring, and clinical monitoring. The fitness monitoring sensors are used to track athletic performance and conditions (e.g., heart rate, number of steps, etc.). These types of monitors do not need FDA approval, so they can be introduced into the market quickly. Clinical monitoring sensors are used to monitor patients for specific clinical purposes and do require FDA approval before being marketed.

Early fitness sensors were very simple, often simply step counters based on threshold detectors applied to accelerometer time series. Then, companies such as FitBit

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began adding heart rate sensors to watches. These sensors are usually light sensors (PPGs) worn on the wrist, a location susceptible to motion artifacts and with less than ideal blood profusion.

Fitness sensors are sometimes used for clinical purposes as well. For example, some athletes wear devices designed to capture signals during exercise that could warn of sudden cardiac death (SCD). "Nearly 58% of SCDs reported between 1980 and 2006 have been reported in basketball and football athletes" [33] – and these deaths typically occur during or immediately after exercise. Similarly, 92% of SCDs in the active duty military population occurred while running in organized physical training events. Thus, having a wearable fabric that can acquire the ECG and blood pressure of the athlete in real time and activate an alerting mechanism when anomalies are detected is highly desirable. The alerting functions could be provided via a linked smart phone for wide area distribution.

Many disease states are difficult to diagnose and manage via periodic clinic visits alone. For example, hypertension is a disease afflicting approximately 30% of the American public "The established office-based approach yields only 50% blood pressure control rates and low levels of patient engagement." [34]. Other therapeutic engagement approaches are needed.

With the availability of PPG and ECG sensors in watches, new screening capabilities are now available, e.g. Apple's ECG sensor on its watch works with its PPG sensor to identify possible atrial fibrillation incidents. AliveCor has received FDA approval to use its ECG sensor to identify patients who have indicators of hyperkalemia [35], a very high potassium level that is found in patients with kidney disease.

A number of useful metrics may be obtained by using different algorithms with signals from a single sensor. For example, a single-lead ECG sensor can be used to obtain measurements such as heart rate, heart rate variability, respiration rate, and indicators of atrial fibrillation. A PPG sensor may be used to measure PRV in pediatric oncology patients in order to predict organ failure [36]. Because PPG sensors are typically cheaper and more widely available, they may be used by more patients than HRV monitoring with an ECG sensor.

B. *Speech*

Speech signals are produced and transmitted by humans on a species-wide scale. Voice signal analysis and feature extraction has yielded effective, and non-invasive, diagnostic tools for a variety of medical indications. Selected examples of current research utilizing speech and voice-based features includes:

Voice spectral/cepstral features associated with Coronary Artery Disease (CAD). Recently, Maor et al. at Mayo Clinic [37] developed a study of patients about to undergo coronary angiography to diagnose CAD (*n=101*). Recordings of each subject were made prospectively, and Mel Frequency Cepstral Coefficients (MFCC's), spectra, and spectrogram features were computed. They found five voice features associated with CAD, and elevated odds ratios, at statistically significant levels.

PTSD detection. Marmar et al. [38] used the SRI pipeline to extract upwards of forty thousand speech features and used random forest algorithms to identify eighteen features associated with PTSD (*n=129*). They achieved an Area Under the ROC Curve (AUROC) of 0.954, and a correct classification rate of 0.891, suggesting that PTSD can be identified from voice features. This study was relatively balanced using ground truth assessments, so the correct classification rate is indicative of low false positive and low false negative rates simultaneously.

Neurological disease detection. There is a research community focused on diagnosis of Parkinson's Disease, and Multiple Sclerosis, using voice-based features, e.g. [39], [40], [41]. There are also research efforts in detecting Alzheimer's Disease e.g. [42], [43], [44].

While the studies noted above are based on small samples of subjects, they all suggest the speech signal as diagnostically useful in applications of neurological, cardiological, and psychotraumatic conditions.

C. *Auscultaton*

Auscultation classically denotes examination procedures in which physicians listened to sounds produced by patients' lungs, heart, and intestines, or even the heart sounds of unborn infants, using a simple stethoscope. This venerable instrument is being reengineered for sound capture, active noise cancellation, graphical displays, and machine learning diagnostic classifiers [45], [46], [47]. This opens numerous signal processing research opportunities in the area which could be of lasting benefit to public health and cost of healthcare.

D. *Ballistocardiograms*

Ballistocardiograms (BCGs) are a "non-invasive technique used to measure the ejection force of blood into the aorta which can be used to estimate cardiac output and contractility change" [48]. BCGs may be taken by using sensors in a bathroom scale [49], by cameras [50], an accelerometer in an ear-mounted device, conductive fabrics and sensors in beds [51], and chairs [52]. The very small movements of the body when the heart contracts are hard to measure and motion artifacts may lead to errors in estimating heart rates [53]. In particular, if the J-peaks of the BCG signals are embedded in noise, serious errors in estimation may occur [54].

Ballistocardiograms are very useful diagnostic tools for patients who cannot tolerate contact sensors, such as severely autistic children [55]. Because they may be mounted in beds and chairs, they may be useful for continuous unobtrusive monitoring to manage chronic disease and diagnose sleep disturbances. Recent work by Kim, et al, indicates that ballisticardiograms may also be used for continuous cuffless estimation of blood pressure [56].

IV. Practical Issues in Mobile ECG Processing

Clinical ECG's are often taken from supine patients on examining tables or beds to minimize motion artifacts. By definition, pervasive sensors operate in the users' environments during their usual activities, possibly including exercise, or other manual exertions. Thus user activities, and pervasive sensors themselves, contribute substantial noise which require robust estimation and detection algorithms.

Majumder [57] indicates that continuous long term health monitoring provides a very important window into various disease states. The available measurements may be combined with predictive algorithms to prevent certain adverse conditions from worsening or even occurring in the first place. Majumder goes on to state that the available sensor products suffer from high signal to noise (SNR) ratios that limit their effectiveness and make it necessary to remove motion artifacts for accurate results.

Majumder, also reports that sensor fusion approaches are being used to assess human emotions, gait and activity, body temperature, oxygen levels, pulse rate and more [58]. Kuwabara, et al, report [59] that a blood pressure monitor may be triggered by an oxygen saturation (pulse oximetry) measurement device to assess sleep apnea. When the subject's oxygen level falls below a certain point, an algorithm automatically triggers a HEM-780 blood pressure monitor to measure systolic and diastolic blood pressure and the subject's heart rate. This allows continuous measurement through the night for better assessment of the risk of sleep-onset cardiovascular events.

As discussed in Chi, et al, motion artifacts are a major problem in using dry electrodes for single lead ECG monitoring. "Resolving the difficulties with motion artifacts remains the unsolved challenge in mobile, wearable ECG/EEG sensor systems." [60]. "The ultimate solution will likely be a combination of some circuit design, but even more a matter of innovative mechanical construction and signal processing. Efforts in that direction are expected to yield significant returns for this field" [61].

Many approaches to health monitoring require sensor fusion, often via smart phone applications. For example, one wearable includes an ECG, "a method for measuring respiration rate, body skin temperature, ambient temperature and 3D body acceleration" [62]. ARM chips are suitable hardware platforms for such devices and small lithium polymer batteries, rechargeable with a micro-USB cable, provide sufficient power for these purposes [63]. ECG measurements may be taken using differential amplifiers with adjustable gain, converted from analog to digital form. This device allows scaling to 8 measured leads for ECG detection [64].

V. A Novel Robust QRS Detection Technique in ECG Processing

A variety of QRS detection algorithms have been developed over decades that have seen massive increases in computing power, and substantial advancements in statistical classification and machine learning techniques. Elgendi et al. reviewed several existing algorithms in terms of noise robustness, parametric tuning (e.g. bandpass upper and lower cut frequencies), and numerical efficiency [65]. Some of these included: simple amplitude thresholds, first and second derivative thresholds, bandpass filtering before first and second derivative thresholding, morphological analysis, Hilbert Transform, and Wavelet methods. The Pan-Tomkins algorithm has been widely used for QRS detection and uses several of the techniques reviewed by Elgendi et al. [66].

We discuss here our approaches to multi-stage robust processing for QRS detection and robust average beat estimation, for ECG's in moderate to very high noise levels which degrade the performance of the algorithms listed in [65] and [66].

We employed a multi-stage noise abatement process starting with clipping and sudden baseline shift noise types. Sudden baseline shifts and impact artifacts can cause slippage of the electrodes, and are often clipped. Affected areas are simply excluded from further analysis, which allows more accuracy and precision in later, e.g. heart rate variability, metrics. Baseline shifts and impact artifacts are detected using an integrator of the low-pass filtered signal with a cut-point of 0.5 Hz, generated with a Butterworth autoregressive filter using 4 poles. Data contaminated with slow baseline wander, mains power noise, and commodity microcontroller self-noise in the ADCs may be retained after high-pass, and notch, filtering, and Least Mean Squares (LMS) adaptive filtering to abate these sources.

Clipping occurs at, or near, the minimum/maximum values for an Analog-to-Digital-Converter (ADC): e.g. 0 and 65335 for a 16 bit ADC. There is hard, and soft, clipping. Hard clipped data simply reads at the ADC minimum or maximum when the input voltage it has saturated the sensor. Soft clipping is more difficult. Some sensors take on a range of values near the min/max values. For soft-clipped data, we employ a constrained maximum likelihood density estimator.

We next employ a multiphase machine learning process that iteratively builds more sensitive and specific QRS detectors in stages. See figure 1. The general progression is from sensitive but non-specific, to sensitive *and* specific detectors as the system learns.

We first apply a bandpass filter (4-12Hz). The bandpass filter is implemented as an autoregressive four pole Butterworth design, which is run both forward and backwards in time to rectify the non-linear phase shifts introduced by this type of filter. We then apply an energy-based detector that doesn't rely on a particular shape or point feature (e.g. maximal slope) over a rolling window 0.15 seconds wide. 0.15 seconds is selected as the median width of the QRS complex with a safety factor. The detector threshold is learned and then applied. Detected QRS regions are normalized, and used as inputs to a machine learning process that constructs the QRS detection filter weights from those regions.

The detection filter is applied and an integrator with a width of 0.15 seconds is used to form a second detector filter from the regions flagged by the first detector filter. Those QRS regions are used in a robust estimator to refine the detector filter weights, and a third iteration of detection filter coefficients are constructed and applied. The maximal points in the detected QRS regions are marked, and then cross-correlated against an averaged QRS from the previous iteration. Finally, a physical plausibility check is performed to reject any physically impossible annotation locations based on what we know about heart physiology and electrical conductance [67] which discusses the physiology of cardiac repolarization. For example, an R-R interval that equates to a heart rate of greater than 220 beats per minute can be construed to involve a false detect. Example double triggers registered by the baseline Pan-Tomkins are shown in figure 2 (bottom).

Finally, depending on conditions, it may be necessary to assess the presence of cardiolocomotor synchronization [68], and to classify events as either QRS complexes or footfalls. Walking and running subjects tend to select cadences that synchronize their heart rates and their stride rates. This can result in synchronized foot fall signals that must be discriminated from actual QRS complexes before creating average beat clusters.

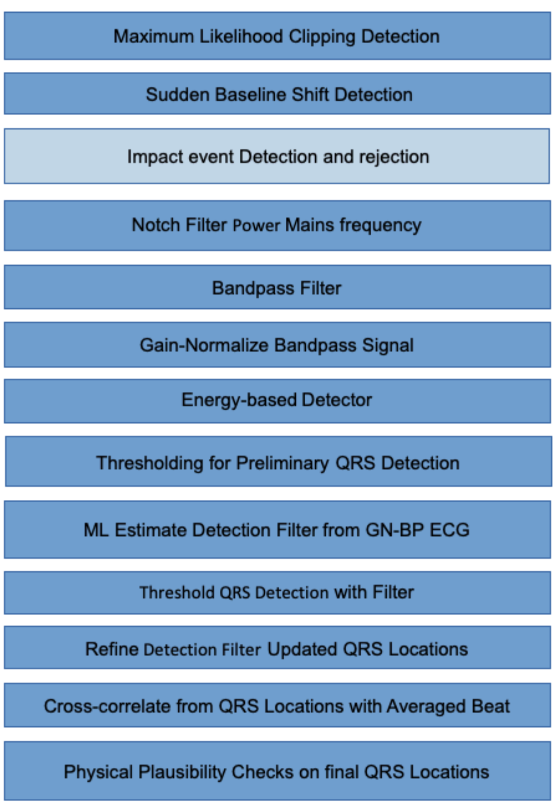

Figure 1. Multiphase Robust QRS detection and estimation processes.

Figure 2 contrasts QRS identifications by the classic Pan-Tomkins versus identifications made by multiphase robust QRS detection. Pan-Tomkins shows a systematic over-detection.

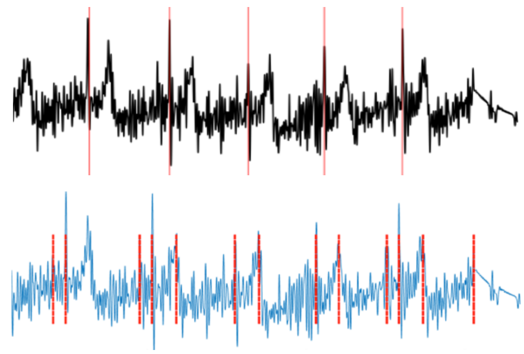

Figure 2. Moderately noisy exercise ECG with Robust Multiphase QRS detection (top) versus conventional Pan-Tomkins detection (bottom). Note the multiple false detections caused by noise using the Pan-Tomkins.

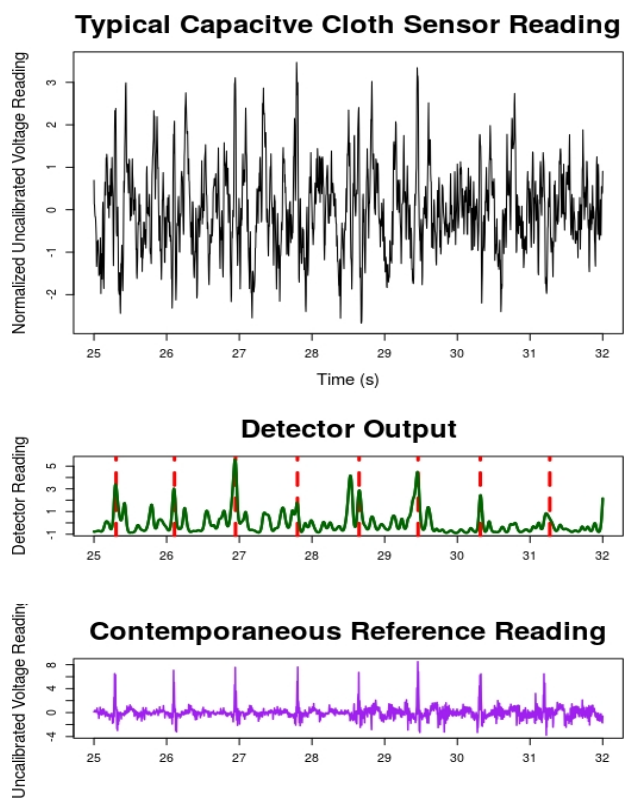

Figure 3. Representative ECG reading from capacitive cloth sensor (top) Robust detector output (middle), contemporaneous ECG recording using contact electrodes from thumb to thumb for ground truth reference (bottom). If the algorithm flags multiple possible locations near each other, as seen between seconds 28 to 29 it will pick the location with the best cross correlation against an estimated average beat.

Figure 3 shows ECG data from a non-contact capacitive sensor operating through layers of clothing. This quality of data can only be processed if robust estimation and detection techniques are employed. We note that the electrode placement in pervasive sensors is convenience based and will seldom correspond to clinical placements of a standard 12-Lead ECG. Thus, the detection algorithms must also be robust with respect to placement variability. There was a contemporaneous contact-based ECG lead recorded as shown in figure 3 (bottom) to provide ground truth for the detectors when operating in high noise as shown in figure 3 (top). We computed Jacard Indices of the QRS detections obtained in the ccontemporaneous reference shown in with detections from:

- A baseline Pan-Tomkins algorithm on the high noise non-contact recording vs. the contemporaneous reference recording which yields a Jacard Statistic of 0.54 in the high noise signal.
- Our robust detection algorithm on the high noise non-contact recording vs. on the contemporaneous reference recording which yields a Jacard Statistic of 0.806 and a true detect rate of 0.893.

The true detect rate for the multiphase robust algorithm over the data set was 89.3 percent, versus 54 percent for the baseline conventional Pan-Tomkins detection algorithm.

The Jaccard index, also known as the Jaccard similarity coefficient, is a statistic used for gauging the similarity and diversity of sample sets. The Jaccard coefficient varies between zero and one, and measures similarity between finite sample sets. It is defined as the size of the intersection divided by the size of the union of the sample sets:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}.$$

VI. Conclusions

The ready availability of commodity sensors including a variety of ECG sensors, microphones, accelerometers, and PPG sensors have opened a wide range of research topics in physiological signal processing which will be of great practical importance. It is also clear that robust signal processing algorithms will be needed to process data acquired in actual user environments to fully exploit these rich data sources.

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