Wireless Medical-Embedded Systems: A Review of Signal-Processing Techniques for Classification

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***Abstract*— Body-worn sensor systems will help to revolutionize the medical field by providing a source of continuously collected patient data. This data can be used to develop and track plans for improving health (more sleep and exercise), detect disease early, and provide an alert for dangerous events (e.g., falls and heart attacks). The amount of data collected by even a small set of sensors running all day is too much for any person to analyze. Signal processing and classification can be used to automatically extract useful information. This paper presents a general classification framework for wireless medical devices and reviews the available literature for signal processing and classification systems or components used in body-worn sensor systems. Examples focus on electrocardiography classification and signal processing for inertial sensors.**

***Index Terms*— Classification, embedded systems, healthcare, signal processing.**

I. Introduction

IN THE past, doctors directly provided long-term personal care to all patients. As medicine became more sophisticated and effective, many other types of caregivers, such as nurses, nurse practitioners, technicians, and specialists have been added to provide better care at lower cost. Healthcare has been commoditized and patients are now treated on a per-complaint basis rather than a whole-life approach, and patients are less likely to develop a long-term relationship with their physician.

In 2007, a group of four prominent physician associations proposed the Patient-Centered Medical Home (PC-MH) initiative to improve patient care and reduce costs while encouraging a longer-term and a more personal physician-patient relationship [1]. The secret to this initiative is using cutting edge technology as a form of virtual caregiver. This technology can be used for communication and care coordination and for ubiquitous and targeted data collection and monitoring. Some of the data required will be added manually by patients or caregivers, but most can come directly from sensors worn by the patient. These sensors can constantly collect relevant and personalized information that will help warn of dangerous health situations such as falls [2] and heart attacks [3] as well as overall health trends [4].

The sheer volume of data from such systems can be overwhelming and it takes innovative signal processing algorithms to extract useful and relevant information. Caregivers do not have the time to personally analyze this data, making it extremely important to automate the process of summarizing the data, highlighting relevant sections, and generating alerts in response to certain observed events. This kind of intelligent data analysis is broadly referred to as *classification* in literature.

This paper evaluates data reduction and classification algorithms developed to support this new generation of medical embedded sensor systems. We start by presenting a generic data processing pipeline for on-body sensor systems which will model most such systems described in literature. We then provide a literature review of techniques and algorithms available for each stage in the pipeline. Particular attention is devoted to examples from electrocardiography (ECG signals) and inertial sensor systems. ECG is interesting because physicians already use portable devices to gather data from certain patients. Furthermore, the signals are well-studied and physicians have very particular ways of classifying and analyzing the data, making it very easy to determine the accuracy of automated classification systems. Inertial sensor systems are promising because many medical conditions affect how people move and act. In addition, motion data is captured from sources distributed around the body, requiring innovative classification techniques. Previous surveys on BSNs [5], [6] focus on reviewing either application development or communication technologies for ubiquitous healthcare. Although signal processing algorithms in this paper are presented in the context of classification, most challenges are generalizable to other applications of the medical embedded systems.

II. Generic Signal Processing Model

In wireless medical embedded systems, sensor nodes are typically attached to the human body in order to collect useful and timely physiological information about their subjects. This configuration is called a Body Sensor Network (BSN). Often, some form of processing is needed to summarize the data and increase the signal-to-noise ratio to make it useful. Similarly, warning systems, such as fall and heart-attack detection systems, must be able to automatically detect events.

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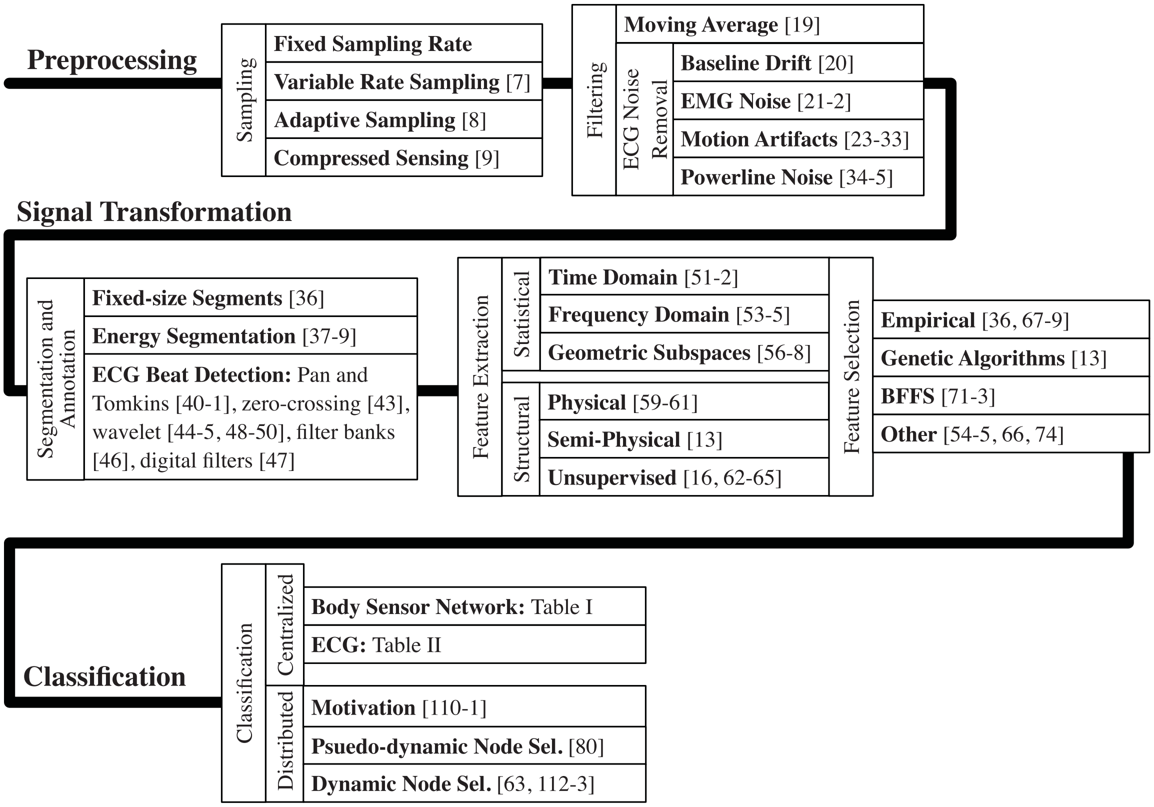

Fig. 1. Generic signal processing flow for classification applications.

Simple statistical tools, such as averages, are not enough since the useful information may be in the morphology of the signal. As example, the important information in an ECG is the shape and relative timing of specific parts of the heart signal. This information can be extracted with pattern recognition (classification) techniques. Complicating matters is the limited battery life of these devices. Wearability favors small devices, and convenience necessitates infrequent recharging. Since the highest power drain is often communication, it is necessary to handle some of the signal processing on the devices themselves.

Fig. 1 shows a generic signal processing model for classification applications. The signal processing flow has four stages. A brief description of each stage follows.

Preprocessing (Section III): Data is sampled from the sensors and filtered. The method and rate of sampling must take into account the application needs and the available hardware. After the data is sampled, it must be filtered to remove noise.

Signal Transformation (Section IV): Signal transformation prepares the data for classification. It starts out by dividing the signal into segments. These segments can represent complete events, or they can be fixed and possibly overlapping intervals. Each segment has a multidimensional (feature) vector extracted from it which will be used for classification. This transformation frequently reduces the data required to represent the segment. These feature vectors can be extracted using statistical or structural techniques. In the statistical processing, a set of statistical and morphological features are extracted from the signal segment. This set is turned into a feature vector. In the structural processing, sensor readings are transformed into a sequence of symbols that preserve physical structure of the original signal.

Centralized Data Processing (Section V): Local data is transmitted directly to a central node for final analysis. Before transmission, some analysis can optionally be done at the local level to reduce that amount of data transmitted. For a single-sensor system, the classification can be done completely locally, making the sensor the same as the central node.

Distributed Data Processing (Section VI): Local decisions that are made by individual nodes are further processed either by a central node (base station) or through collaboration of the sensor nodes (in-network processing) to generate a final decision about the current action. For instance, in action recognition, a final decision can be made using either a data fusion or a decision fusion scheme. In the data fusion scheme, features from all sensor nodes are fed into a central classifier. The classifier then combines the features to form a higher dimensional feature space and classifies movements using the obtained features. In the decision fusion approach, however, each sensor node makes a local classification and transmits the result to a central classifier where a final decision is made according to the received labels.

Variations: This is the basic outline of the flow and transformation of data that is initially captured by the sensors and eventually used. While it is possible to perform all but the distributed data processing on the local sensor nodes, it's possible to transmit data from a previous step and perform these steps somewhere else. Many of these steps may be performed in a distributed manner: for instance, segmentation sometimes depends on data sharing between sensor nodes to ensure that all sensor nodes use the same segments. Also, many of these steps are optional, with filtering and local information extraction commonly left out.

III. Preprocessing

Preprocessing includes decisions about how and when to sample sensor data and noise filtering. Preprocessing is about transforming the signal in bulk without separating out events or classifying the data. This preprocessing prepares the data for later steps. Even in pure monitoring applications where no classification is performed, these steps are still required.

A. Data Sampling Approaches

There are several methods of sampling: fixed-rate, variable rate, adaptive sampling, and compressed sensing. Furthermore, if required, the bit resolution of sensor readings can be tuned in order to lower power consumption of the analog-to-digital converter.

1) Fixed Rate Sampling: The most convenient and simple form is fixed-rate sampling. However, if the hardware supports it, some of the other methods can decrease power required for sampling or communication. For fixed-rate sampling, the sampling frequency must be chosen to satisfy the Nyquest criterion.

2) Variable Rate Sampling: A variable sample rate generator can be designed to produce different sample rates for variable resolution [7]. It consists of a clock generator, sampling circuit, and a multiplexer. The clock generator generates highest needed sample rate, and then sends it to the sampling circuit and the multiplexer. The sampling circuit produces several clocks, each at half the frequency of the previous and then sends them to the multiplexer. The multiplexer chooses the clock with a sample rate select signal from MCU. This design provides the capability of variable rate sampling. The rate can be changed dynamically based on power needs and the current type of analysis.

3) Adaptive Sampling: Adaptive sampling is based on variable rate sampling, but automatically changes the sampling rate based on the data. It is a practical method to reduce the sample data volume since the frequency contents of the signals vary with time. In [8], a low-power analog system is proposed, which adjusts the converter clock rate to perform a peak-picking algorithm on the second derivative of the ECG signal.

4) Compressed Sensing: The work proposed in [9] for packet loss mitigation is based on Compressed Sensing (CS), an emerging signal processing concept, wherein significantly fewer sensor measurements than that suggested by Nyquist sampling theorem can be used to recover signals with arbitrarily fine resolution. CS relies on the assumption that the signal of interest is sparse in some basis representation with only M non-zero elements, where $M \ll N$ and N is the signal dimensionality. Many medical signals are sparse, making them ideal for this type of sampling.

B. Sampling Rate and Resolution

Researchers use a variety of bit rates depending on the application and problem constraints. Certain researchers have investigated the effect of sampling frequency and bit resolution for classification of human modes of locomotion using body-worn acceleration sensors [10]. They have shown that good recognition performance can be achieved with $20Hz$ sampling frequency and 2 bit-resolution without much impact on the recognition performance. Other studies have also reported a sampling rate of around 20 Hz for analyzing human movements [11]–[13].

Using a more analytical approach based on power spectrum, it has been shown that in most cases a sampling rate between 40 Hz and 50 Hz is sufficient for analysis of human movements [14]–[16]. In these studies, power spectrum graphs were used to find the highest frequency of the signal, suggesting a sampling frequency of twice the highest frequency of the signal would suffice to meet the Nyquist frequency. For ECG signals, typical sampling rates range from 250 to 500 Hz [17] or even up to 1000 Hz when high time-frequency resolution ST segment analysis is required, while the resolution of the quantizer could be as low as 10 bits or as high as 24 bits [18].

C. Filtering

The level of complexity of the filtering algorithm highly depends on the application of interest and the type and quality of sensor readings. In many cases, a simple moving average filter would suffice to reduce the effect of noise. One such applications is use of accelerometer sensors for movement classification. In contrast, if details of the signal affect the outcome of the classification algorithm, more complex filtering is required in order to clean the signal. One application with these requirements is monitoring ECG signals.

1) Moving Average: For personal health monitoring [19], the raw accelerometer data is filtered and preprocessed. The filtering includes a moving average filter to eliminate high frequency movement artifacts, and separate the low and high frequency components of the acceleration signal. The choice of the window size for the moving average filter relies on two objectives 1) the cutoff frequency needs to be low enough to effectively bypass unnecessary motions such as tremors that occur at higher frequencies than normal movements and 2) the cutoff frequency must be high enough to capture the data of interest.

D. ECG Filtering

ECG signals are a perfect case study for different filtering techniques. A number of specific noise categories have been identified, and a significant body of research has been built around filtering techniques needed to remove each type of noise. In the following paragraphs, various noise sources and the method of removing or identifying them are presented.

1) Baseline Drift: Baseline drift appears as a very slow varying frequency component causing the ECG waveform to wander in levels much greater than the nominal amplitude of the regular ECG waves. This type of noise is mostly caused by respiration which modulates the impedance between the measuring electrodes. Since this type of distortion is concentrated in frequencies below 1 Hz, it can be removed with a high-pass filter. However, a finite impulse response (FIR) filter that can efficiently remove frequency components below 0.5 Hz in a signal sampled at 250 Hz or even more needs a very large number of coefficients, making it impractical for resource-constrained real-time systems. An alternative would be to employ an infinite impulse response (IIR) filter which requires less coefficients but in that case there are two major concerns: (a) IIR filters may cause unwanted distortions in signal morphology and (b) implementation of IIR filters on fixed-point microprocessors is challenging since IIR filters are very sensitive to coefficient quantization (as a result a hardware implementation of the filter might be preferable). Another way of removing baseline drift is to employ the Discrete Wavelet Transform (DWT) up to a certain scale, which essentially acts as a filter bank on the signal and to zero-out the coarsest scales approximation coefficients that correspond to the lowest frequency components in the signal [20].

A different approach is to utilize median filtering to remove the DC drift. In this case a moving median filter is employed in order to remove P, QRS and T waves from the trace. The residual is the pure baseline drift which can then be subtracted from the original signal. In this case, care needs to be taken in choosing the appropriate window size for the filter. This choice can significantly affect the quality of the filtered signal, since a window size that is not big enough will tend to remove significant information from the smaller waves, e.g. the P and T waves. This can be seen in Fig. 2 where a segment from the Record 212 of the MIT-BIH Arrhythmia database (which can be accessed at Physionet [17]) has been plotted along with the result of employing a median filter that is equal to 1 second of sampling, 1/2 a second and 1/4 of a second.

2) EMG Noise: EMG noise is interference on the ECG signal due to muscle contractions. EMG induced noise presents a more challenging issue, since this type of noise can spread through the frequencies of interest in the ECG. In this case, exact reconstruction of the original distortion free signal is impossible, so the challenge now is to quantify the amount of noise in the waveform and to decide whether it is still clinically usable or corrupted to such a level that it should be constituted unusable. An efficient method for reducing noise components spread across the whole signal spectrum is wavelet thresholding [21]. This technique comprises of the following steps: Discrete Wavelet Transform (DWT); Scale-dependent threshold estimation; Thresholding; Signal reconstruction from the thresholded coefficients. Wavelet denoising can be utilized to remove efficiently in-band noise (even power-line interference). The redundant version of the wavelet transform which is referred to as undecimated or stationary wavelet transform (UWT or SWT), will yield better results at the expense of more computations. This can be seen in Fig. 3 where a clean ECG has been contaminated with white noise resulting in 5 dB SNR. UWT denoising yields an SNR of 14.51 dB, while DWT results in 12.69 dB and more signal distortions. However an important issue to note here is that denoising algorithms or filters tend to introduce unwanted distortions in the ECG waveform [22]. These distortions might not be easily identifiable with visual inspection and they can also distort the values of clinically relevant signal features, which in the worst case might affect the final ECG classification. As a result when employing such algorithms in a clinical scenario whereby the ECG trace will be used for more than just heart rate estimation, the effect of the de-noising procedure will need to be carefully evaluated.

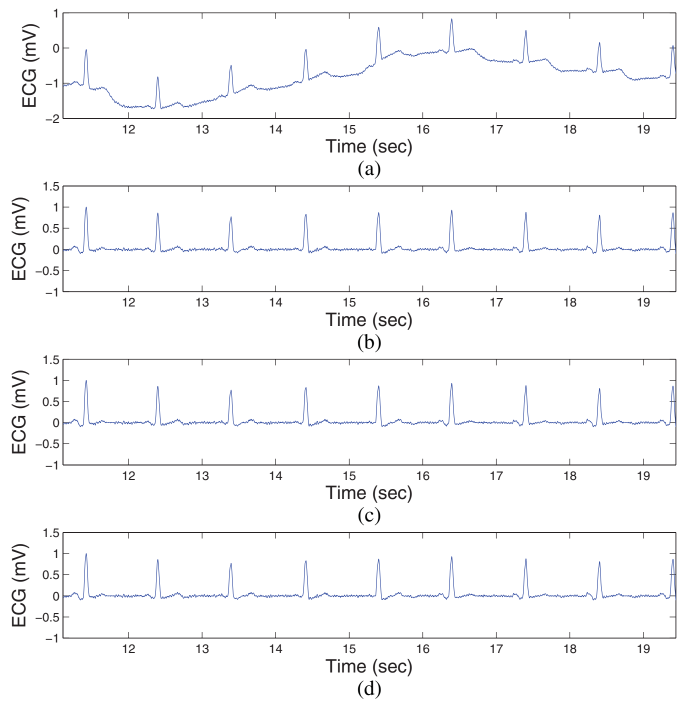

Fig. 2. Effect of the median filter's window length on the reconstruction quality of the ECG. (a) Original signal. (b) Median filtering (window length = 1 sec). (c) Median filtering (window length = 1/2 sec). (d) Median filtering (window length = 1/4 sec).

3) Motion Artifacts: Motion artifacts can introduce severe noise in the signal and can, in the worst case, corrupt it to such an extent that it might be rendered clinically unusable. In such a case, appropriate logic needs to be utilized to detect such cases [23], otherwise if we fail to identify such events the result will be erroneous feature extraction and thus incorrect parameter estimation and pattern classification. This type of interference can be very effectively removed if a continuous and reliable noise reference is available. In that case adaptive filters can be used to reject the unwanted signal components [24].

As mentioned above, if the noise component has severely corrupted the information content of the ECG signal, intelligent algorithms could be utilized to identify these cases. In 2011, the Computing in Cardiology Conference [25] hosted a challenge for the development of such an algorithm [26]. Several near real-time algorithms were developed that utilize various features to identify corrupted ECG traces. Examples of features include the distribution of the frequency content of an ECG waveform, the autocorrelation of a signal or the cross-correlation between different ECG leads, statistical features of an ECG signal such as higher order moments and the performance of beat detection algorithms across multiple leads [27]–[29].

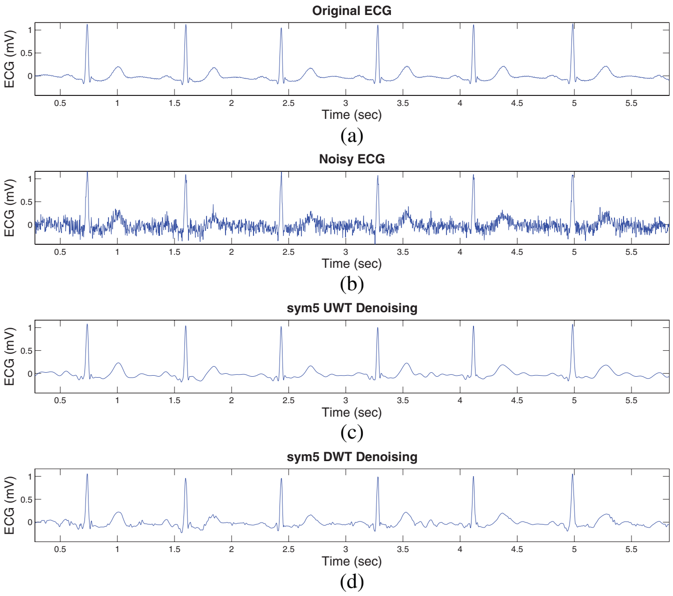

Fig. 3. (a) Noise-free ECG. (b) ECG with AWGN (5-dB SNR). (c) UWT denoised ECG (14.51-dB SNR). (d) DWT denoised ECG (12.69-dB SNR).

Artifacts in the ECG can also be very effectively removed by utilizing the redundancy of multiple simultaneously recorded ECG leads. In that case well-known algorithms such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA) can be employed to decompose the multi-channel signal in several orthogonal or independent components [30], [31]. The next step is to identify the signal components that correspond to noise and then after eliminating those components the denoised version of the signal is acquired by reversing the transformation. The major drawback of such algorithms is their computational complexity and the fact that they cannot be run in real-time.

Finally, an alternative approach to artifact removal from the ECG is model-based filtering. Sameni et al [32] developed a Bayesian filtering framework based on a non-linear ECG model whose parameters are estimated on-line using a Kalman filter. A similar approach is presented in [33] where the authors make use of an adaptive Kalman filter that makes use of an estimation of the measurement noise to enhance ambulatory ECG recordings.

4) Power-Line Interference: Power-line interference introduces a noise component centered around the power-line frequency (e.g. either 50 Hz or 60 Hz). This type of distortion can be efficiently removed with an IIR notch filter [34]. Such a filter can be efficiently implemented on resource constrained platforms by utilizing multiplier-free recursive running-sum filters [35].

IV. Signal Transformation

In the signal transformation step, the data is transformed into a form more useful for classification. First, the signal is divided into segments, then a multi-dimensional feature vector is extracted from each segment. The segments may be either overlapping or mutually exclusive. In many cases, segments are chosen to represent a complete event such as a full heartbeat, a complete motion, or a possible fall event. Each segment is assigned a vector of numbers extracted based on the signal data in the segment. This vector is called the feature vector and can either be extracted using statistical or structural methods. This vector is used in the next step to classify the segment.

A. Segmentation and Annotation

Many information processing and extraction algorithms, such as classifiers, are designed to extract information about specific events or discrete time intervals. Segmentation algorithms divide continuous data streams into discrete time intervals of the type expected by the information processing step, while annotation algorithms locate and label specific events. Segmentation implicitly filters out time intervals with nothing of interest. For simplicity, segmentation is often discussed as a separate step from information processing, but in many instances a feedback loop between the segmentation module and the information processing module is required for precise segmentation. Several segmentation techniques are presented.

1) Fixed Size Segments: Segmentation is approached in a variety of ways in the literature. The simplest method is to use fixed-size segments. This is computationally simple, but does not divide the signal in a meaningful way. It is appropriate for long-duration actions that are stationary or cyclo-stationary. Several authors classify fixed-size segments independently of other segments [36]. This can result in outliers and discontinuities. This approach is simply impractical for signals that have specific predefined morphology such as ECG.

2) Energy-Based Segmentation: Another approach is to look at the energy content of the sensed data. Quwaider and Biswas [37] divide actions, which they refer to as postures, based on the activity level measured with accelerometers. With high-activity postures, such as running, the postures are identified based on energy level on each limb. For relatively quiet postures, such as sitting and standing, they employ a Hidden Markov Model used on radio signal strength differences between sensor nodes. With this they can differentiate between sitting and standing postures. Other possibilities include using the signal energy for segmentation, or an unrelated source of data. In [38], the standard deviation was used to label intervals as actions or rests for each sensor. While this worked well for actions separated by inactivity, sometimes actions often occur one after another with no separation. Sometimes independent data can be used to easily segment actions using energy. For instance, Ward et al. recognized several workshop activities such as taking wood out of a drawer, putting it into the vice, getting out a hammer, and more. They avoided the problem of segmenting accelerometer data by segmenting the data using the presence or absence of sound, and then identified the action using accelerometer data and a Hidden Markov Model (HMM) classifier [39].

3) ECG Beat Detection: Heart beat detection mainly consists of determining the onset of the R wave in the QRS complex. A key observation here is that the bandwidth of the wave of interest (e.g. the QRS complex) is mainly concentrated in the 1-40 Hz frequency range. As a result, it is therefore a good strategy to apply appropriate filters that will isolate these frequencies and that will diminish the contribution of other spectral components, e.g. P and T wave, baseline wander, etc. Perhaps the most well-known algorithm for the task of ECG beat detection is the one by Pan and Tomkins [40], which was later refined by Hamilton and Tomkins [41]. This algorithm comprises of the following stages: Low-pass filtering, High-pass filtering, Differentiation, Squaring, Moving-average, Rule application and adaptive thresholding.

The advantage of this algorithm is that the filters it utilizes are computationally inexpensive (small number of coefficients which are also all powers of two) and that the logic required to detect a beat is simple, the algorithm can thus be implemented in real-time with a small time delay (which is mainly introduced by a search back algorithm to remove spurious detections). The steps described above for detecting the R peaks is illustrated in Fig. 4 and Fig. 5.

A wide variety of other methods for QRS detection exist in the biosignal processing literature. A very good review of software based methods for this task is given by [42], where not only the accuracy (given the fact that the recorded sensitivity of the Hamilton-Tomkins detector is 99.69% [41]) but also the computational complexity and real-time operation of each method is evaluated. Examples of other popular techniques for R peak identification include: counting the zero-crossings [43], wavelet-based methods [44], [45], filter-banks [46] and digital filters [47].

The method described in [45] which utilizes the wavelet transform, has been extended by Martinez et al. [48] and this newer version has been successfully implemented in [49] on an embedded wearable sensor platform where it can operate in real time. This technique consists of decomposing the ECG signal in multiple scales and then employing mathematical properties of these decompositions to detect irregularities (such as high-frequencies, i.e. peaks) that are consistent across several scales. Finally, Tabakov et al. [50] have also implemented an online digital filter approach for ECG filtering and QRS detection, which yields high accuracy and is also operational in real-time.

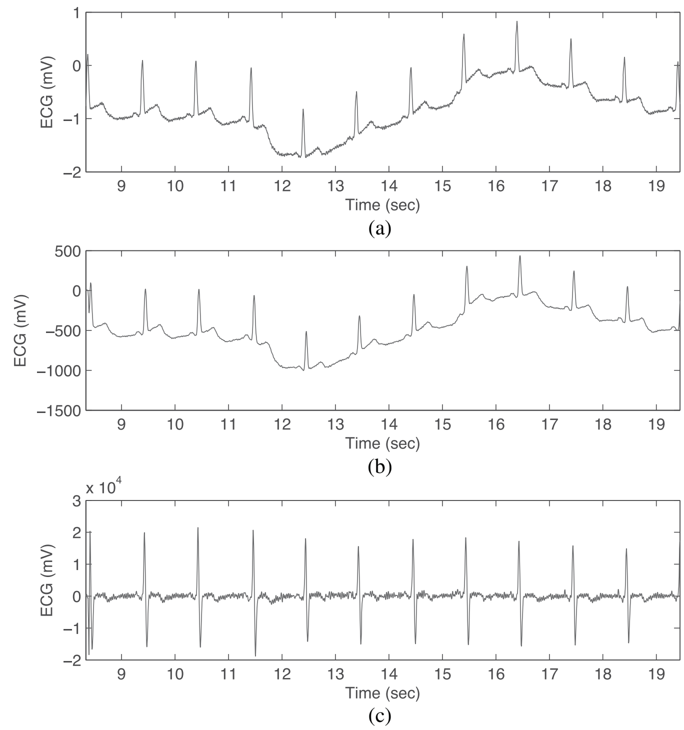

Fig. 4. First two steps of the Pan–Tomkins algorithm. (a) Original signal. (b) Band-filtered signal. (c) Derivative of band-filtered signal.

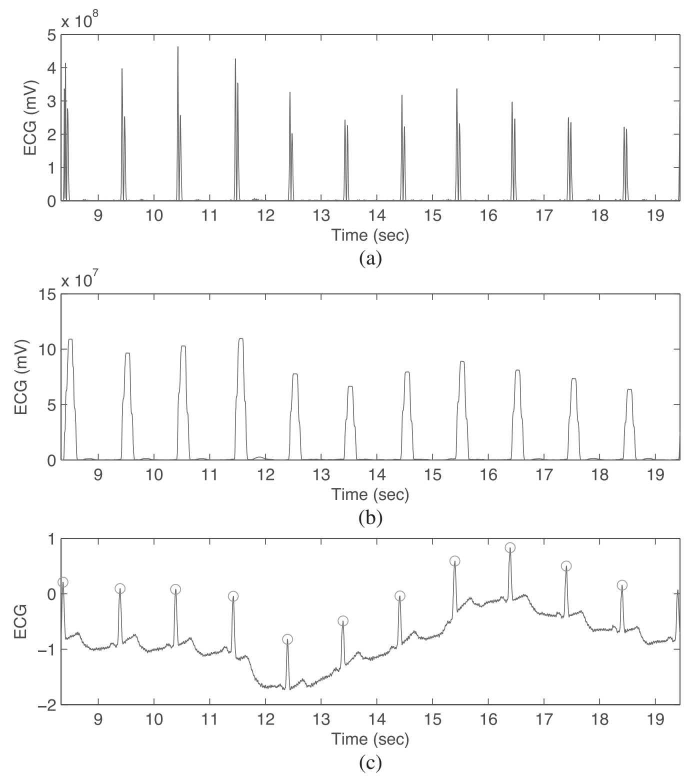

Fig. 5. Final three steps of the Pan–Tomkins algorithm. (a) Squared signal. (b) Moving average. (c) Peal detection.

B. Statistical Feature Extraction

The primary goal of recognition algorithms is supervised or unsupervised classification. The design of a recognition system requires careful attention to the information extraction. Among the various frameworks in which information extraction has been traditionally formulated for recognition systems, the statistical processing approach has been most intensively studied and used in practice. In the statistical processing, the input data will be transformed into a reduced representative set of features. If the extracted features are carefully chosen, it is expected that the features will contain the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

In the BSN systems, the statistical feature extraction algorithms can be grouped in three main categories. 1) Time-domain features, 2) Frequency-domain features, and 3) Geometric subspaces.

1) Time-Domain Features: Authors in [51] proposed a feature extraction method based on genetic programming to extract discriminative features robust to sensor displacement for activity and gesture recognition from body-worn acceleration sensors. The extracted features from each sensor node are statistical time-domain features including mean value, variance, signal energy, zero crossing rate and correlation between different sensor axes.

In [52], feature extraction of the ECG biometrics is carried out as follows: Firstly, the RR interval values are extracted. Secondly, each RR value is quantized to a positive integer of w bits, where w is a quantization parameter. Thirdly, a set is obtained in the timing order where the elements are m consecutive quantized RR values. In this way, the ECG biometric features are finally represented as an ordered set.

2) Frequency-Domain Features: Studies show in gait recognition both magnitude and phase spectra are effective gait signatures. In [53], authors proposed a gait recognition approach using spectral features of horizontal and vertical movement of ankles in a normal walk. They used an integration of magnitude and phase spectra for gait recognition using AdaBoost classifier. At each round, a weak classifier evaluates each magnitude and phase spectra of a motion signal as dependent sub-features, then classification results of each sub-feature are normalized and summed for the final hypothesis output.

Authors in [54] investigate ear-worn accelerometers for the development of a gait analysis framework. In order to observe the multi-resolution properties of the acceleration signals across both time and frequency, the wavelet transform was used. The DWT coefficients were selected that provide a compact representation of a signal in time and frequency that can be computed efficiently ($O(n)$).

To reduce the dimensionality of recorded data, authors in [55] extracted a set of features for tracking of human activities. The feature set consists of frequency and time domain features which includes linear and mel-scale FFT frequency coefficients, cepstral coefficients, spectral entropy, band pass filter coefficients, integrals, mean and variances.

3) Geometric Subspaces: An information-theoretic criterion is introduced for training a feature extractor independently of the classifier in [56]. The proposed method uses nonparametric estimation of Renyi's entropy to train the extractor by maximizing an approximation of the mutual information between the class labels and the output of the feature extractor.

Authors in [57] described a gait classification techniques based on data obtained using a body area sensor network platform named TEMPO 3. They used a linear feature extraction technique named MRMI-SIG that is optimized to separate data classes. In [58], in order to diagnose cardiac abnormality such as Ventricular tachycardia, authors applied a novel system to analyze and classify compressed ECG signal by using a PCA for feature extraction and k-mean for clustering of normal and abnormal ECG signals.

C. Structural Feature Extraction

In structural feature extraction, all data is evaluated according to a set of rules. These rules can be based on a physical model or obtained through pattern recognition techniques. Structural feature extraction matches the data to a model. In the *physical model*, the model is based on human analysis and physics and the matching works by matching the sensed data to expected data. In the *semi-physical model*, the data is matched to a predefined model using standard pattern recognition techniques, such as a HMMs. Finally, in the *unsupervised structural model*, the model itself is determined with unsupervised pattern recognition techniques.

1) Physical Model: Fitting observations to a model, can be used as one method to interpret human motion. For most object model recovery, the process should be insensitive to lighting, position, and size. In modeling human motion, the recovery process should not be sensitive to clothing or any other features specific to a particular individual. Furthermore, unlike most objects, the human body is composed of a large number of parts which can move non-rigidly with respect to one another.

Using gait as a biometric is of increasing interest since it is non-invasive and can be measured without subject contact or knowledge. In [59] and [60], the dynamics of the models are derived from medical studies, which indicate that human gait is periodic, with the rotation pattern of each thigh during a gait cycle being approximately sinusoidal in nature.

In [61], the wearable sensors of a BSN are attached at the exterior side of the thigh. The hip angle, θ, is defined as the angle between the thigh and gravity direction. The swing velocity (angular velocity) of the thigh is $v = d\theta/dt$. Kalman filter is applied to estimate θ and v, which are key features of the gait cycle. By fitting the sensed data to the model, appropriate gait features and events can be found.

2) Semi-Physical Model: Another approach is to extract events based on an existing physical model using pattern recognition. Authors in [13] introduce a generic method for temporal parameter extraction called the hidden Markov event model based on HMMs. Their method constrains the state structure to facilitate location of key events of gait.

3) Unsupervised Structural Model: The additive hierarchical representation of human movements is very similar to the representation of human speech: raw sounds are divided into phonemes, which are further grouped into words, which are grouped into sentences [62]. Phonology exclusively focuses on sound, ignoring physical movement of the tongue and throat and cues from facial expressions. Similarly, raw sensor data can be used to build sequences of motions, which can be further grouped into actions and then activities. The purpose of structural processing is to transform inertial sensor readings into a sequence of temporal primitives, called movement transcripts. This idea has been used by several authors [16], [63], [64] and proved effective for many applications of inertial sensors. The goal is to capture structural properties of the signal by extracting statistical feature from individual data points and grouping data points that are similar in the feature space.

Fig. 6 shows a transcript of a synthetic one-dimensional signal which illustrates correspondence between the primitives and signal patterns (figure taken from [63]). In this figure, corresponding primitives are generated with a Gaussian Mixture Model (GMM) clustering approach, labeled and colored. For example, primitive 'G' corresponds to a portion of the signal

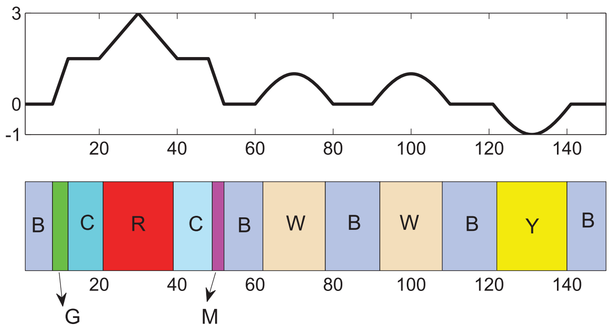

Fig. 6. Example of motion transcripts generated for a 1-D synthetic signal [63].

with a positive slope and 'W' represents a portion with positive value of the second derivative.

Neurologists classify brain function and functionality based on the structure and timing of electrical brain activity. This is frequently recording using electroencephalography (EEG). Researchers in [65] automated this analysis by performing unsupervised spatio-temporal clustering of EEG signals which were then put through a wavelet decomposition to form templates. A supervised approach was used to select the most relevant templates for the experiment. These templates could then be used to classify the signal in real time.

D. Feature Selection

The problem of feature extraction is sometimes followed by the feature selection problem: given a set of candidate features, selecting a subset that performs the best under some classification system. This procedure can reduce not only the cost of recognition by reducing the number of features that need to be collected, but in some cases it can also provide a better classification accuracy due to finite sample size effects. In the context of BSNs, feature selection implies less data transmission and efficient data mining. It also brings potential communication advantages in terms of packet collisions, data rate, and storage.

In [66], feature selection was based on visual and statistical analysis. The features were visually compared against annotation to find good candidate features. Distribution bar graphs of each feature signal during different activities were plotted for comparison. *A priori* information was used in the quest for the best features. As a result of the feature selection process, at the end, only six features were selected for classification.

Most early studies for activity recognition are based on empirical feature selection techniques [36], [67]–[69]. Recent studies have adopted more systematic feature selection techniques for enhancing the classification of activities.

Authors in [54] used wavelet coefficients to extract both time and frequency properties of the acceleration signals. Due to the fact that a large feature space was generated from the digital wavelet transform, supervised feature selection was used in order to select the useful features. In this work, the Iterative Search Margin Based algorithm proposed by Gilad-Bachrach et al. [70] was used. A margin is a geometric measure for evaluating the confidence of a classifier when making a decision.

Genetic algorithms (GAs) can be used for feature selection and model parameterization. The algorithm in [13] introduces a generalized method for event annotation in walking based on HMMs. GAs start with a random population of solutions. Over several generations, they crossover (mate) and mutate the solutions, weeding out inferior solutions in a stochastic manner. Each solution is represented by a vector of selected features.

Authors in [55], present a hybrid approach to recognizing activities, which combines boosting to discriminatively select useful features and learn an ensemble of static classifiers to recognize different activities, with HMMs.

BFFS (Bayesian Approach for Feature Selection) is a filter based feature selection method developed at Imperial College. In [71], the use of BFFS for optimum sensor location selection is presented. In this work, general activities are recorded with body-worn acceleration sensors. To evaluate the performance of BFFS, a multi-layer Self-Organizing Map (SOM) [72] with temporal information was employed as the classifier. In [73], The BFFS was used to rank the relevance of features to different human activity classes.

To reduce the time and energy required to calculate the feature vector, several subsets of the complete feature space were evaluated in [74]. The Correlation based Feature Selection (CFS) method was used to find feature sets containing features that are highly correlated within the particular class but are uncorrelated with each other.

V. Centralized Data Processing

While the data collected by the sensor nodes can be processed in a distributed manner, most existing works focus on developing algorithms for local processing of the data and using a data fusion scheme at the base station for summarizing state of the system. In fact, research on distributed and collaborative signal processing in the area of body sensor networks is in an early stage. In a local processing paradigm, each sensor node performs partial processing on the data and transmits the results to a base station. For action recognition, for example, the base station is responsible for combining data from all the nodes and building a centralized classifier which identifies unknown actions. The accuracy of such a classifier depends on a variety of parameters including the classification algorithm, sensor node placement, types of features that are extracted from the signal, and number and type of actions/activities that are going to be recognized. For example, in [75], authors report the results of a study on activity recognition using different types of sensory devices, including built-in wired sensors, RFID tags, and wireless inertial sensors. The analysis performed on 104 hours of data collected from more than 900 sensor inputs shows that motion sensors outperform the other sensors on many of the movements studied. A prototype called *MEDIC*, developed in [76] for remote healthcare monitoring, uses a PDA as the base station and several sensor nodes that collect and process physiological data. They use a Naive Bayes [77] classifier that provides more than 90% accuracy. A wireless body sensor system for monitoring human activities and location in indoor

TABLE I
WORKS ON ACTION RECOGNITION

Ref.	Classifier	No. Nodes	No. Actions	Accuracy	Node Location
[82]	kNN	6	7	91%	Shoulder, Chest, Waist, Back, Wrist, Ankle
[83]	kNN	1	4	84%	Chest
[81]	kNN	8	25	97%	Waist, L-wrist, R-wrist, L-arm, R-thigh, L-thigh, R-ankle, L-ankle
[81]	kNN	5	25	96%	L-wrist, R-wrist, L-thigh, R-ankle, L-ankle
[81]	kNN	2	25	92%	Active nodes are detected dynamically
[74]	kNN	1	4	85%	Pocket
[74]	kNN	1	4	86%	Necklace
[74]	kNN	1	4	87%	Belt
[74]	kNN	1	4	87%	Wrist
[74]	kNN	1	4	89%	Shirt
[74]	kNN	1	4	92%	Bag
[84]	HMM	19	10	98%	R-arm (10 nodes), L-arm (9 nodes)
[84]	HMM	3	10	97%	R-forearm, L-forearm, L-arm
[84]	HMM	1	10	80%	Active nodes are detected dynamically
[79]	HMM	3	8	90%	Shoulder, Waist, Wrist
[85]	HMM	3	19	92%	Waist, Wrist, Thigh
[86]	HMM	8	25	93%	L-wrist, R-wrist, L-arm, R-arm, R-thigh, L-thigh, R-ankle, L-ankle
[87]	SVM	6	6	95%	Shoe (1 accelerometer. & 5 pressure sensors)
[88]	SVM	2	9	79%-97%	Hip (accelerometer), Chest (2 ECG electrods)
[89]	SVM	1	8	84	Waist (mobile-phone)

environments is introduced in [78] where each sensor node is equipped with accelerometer, gyroscope and magnetometer. Authors in [36] use a network of five accelerometers to classify a sequence of daily activities. They report a classification accuracy of 84% for detecting twenty actions. The system in [79] uses seven different sensors embedded in a single node to classify twelve movements. The accuracy obtained by this system is 90%. Furthermore, the accuracy reported by the centralized k-NN classifiers in [80], [81] is more than 90% for classification of different human actions.

A. Activity Information Extraction

While many algorithms including k-Nearest Neighbor (k-NN) [74], [81]–[83], Hidden Markov Models (HMM) [79], [84]–[86], Naive Bayes [76], [90], Support Vector Machines [87], [88] and others [68], [91] have been investigated, the k-NN and HMM are more common in action recognition in wireless healthcare domain when motion sensors are used as primary means for information inference. Table I shows a summary of most recent works on action/activity recognition from wearable sensors. The k-NN algorithm classifies an unknown action based on its distance to closest action in the feature space. The distance measure is determined according to the type of features. Most common measures include Euclidean distance, used for numerical features [12], and edit distance, used for alphabetical attributes [63]. Advantages of the k-NN include simplicity and scalability [81] which makes it feasible for practical uses of wearable healthcare platforms.

Frame-based classifiers such as the k-NN classify each segment independently. HMM-based classifiers are attractive because they can take advantage of temporal properties of the observed data. For instance, a person may not sit down twice in a row because the action of sitting down must start from the standing position. Also, an individual may be more likely to go from running to walking than from running to sitting down, despite the fact that both are possible. HMM-based classifiers can represent these situations by inducing a statistical model for detecting the most probable sequence of events occurring during system operation. Hidden Markov Models consider a system that can be modeled with a set of discrete states. The system is always in exactly one state. The output of the system (sensor data) is probabilistically based solely on the present state. At each cycle, the system produces an output and a state transition occurs. In health systems, actions could be represented by individual states, by sequences of states, or by the transition between states [92]. As an example, postures, such as "sitting," "standing," and "lying down" produce fairly consistent and static data, and thus can be represented by individual states [37]. A complicated action such as swinging a tennis racket might be modeled using a sequence of states [86], [93]. Finally, transitional actions, such as sit-to-stand may either be modeled with a sequence of states starting and ending on the appropriate postures, or even exclusively using the starting and ending postures [86].

More recently, researchers have started integrating other sensor modality with accelerometers and gyroscopes to infer activities and postures. [87] and [88] use pressure sensors and ECG sensors respectively, in addition to the motion sensors, to perform activity recognition and posture identification.

B. ECG Information Extraction

Beat classification corresponds to the process of determining whether the detected ECG beat is of normal origin or if it displays some abnormality, such premature ventricular

TABLE II
COMPARISON OF ECG CLASSIFICATION TECHNIQUES

Reference	Feature	Classifier	Accuracy	Beat Types[1]
[98]	Statistics over Wavelet features	Probabilistic Neural Network	99.65%	N, V, L, R, A, P
[97]	Hermite-basis function projections	Self Organizing Map	98.5%	All
[99]	Standard Morphological	Decision Trees	96.13%	All
[100]	Raw Data Samples	Multi Layer Perceptron	98.07%	N, R, V, P, F
[101]	Custom Morphological and Matching Pursuits	Kth Nearest Neighbor	98.44%	N, V, L, R, P
[102]	Higher-order statistics	Fuzzy Hybrid Neural Network	96.06%	N, V, L, R, A, I, E
[96]	Standard and Custom Morphological	Linear Discriminants	86.2%	All
[103]	Matching Pursuit based	Multi Layer Perceptron	98.7%	N, V, L, R, P
[104]	ECG Clinical Features	Layered HMM	99.2%	N,V

[1]N = Normal Beat. V = Premature Ventricular Contraction. L = Left Bundle Branch Block. R = Right Bundle Branch Block. A = Atrial Premature Contraction. P = Paced Beat. I = Ventricular Flutter Wave. E = Ventricular Escape Beat. F = Fusion of Paced and Normal Beat.

contraction or ectopic systole. As arrhythmic patterns tend to appear infrequently, long-term 24-hour ECF recordings are often used to detect the occurrence of arrhythmic patterns, which can be of high clinical importance. Manual analysis of such ECG records is a tedious task, thus automatic interpretation is particularly significant.

Computer-based analysis and ECG classification has been widely addressed by the biomedical research community during at least the last three decades [94]–[96]. As a result, nowadays there is an abundance of ECG classification algorithms in the literature. However, not all of these methods are applicable in the context of wearable health monitoring systems.

ECG classification requires the generation and the selection of appropriate features that can represent efficiently and compactly the ECG beat classes of interest. As discussed in the previous section these features can be extracted a) in the time domain, b) in the frequency domain or c) the can be a representation or projection of the beats in a different domain. Examples of type a) features include wave and segment widths (usually denoted as ECG clinical features) and heights which can be extracted via any of the available ECG delineation techniques that were introduced in section IV.A. Additional time-domain features include QRS slopes, QRS area, RR interval statistics, vectorcardiographic features or even raw time-domain samples. Frequency domain features include information about the distribution of the Fourier spectrum of a specific beat. Finally a variety of alternative features have been investigated by different research groups. Examples of such features include wavelet statistics, linguistic representation of ECG segments and projections onto Hermite basis functions. These features are then utilized to train some type of classifier, usually supervised as there is by now a wide range of annotated ECG signals [97]. Classification methods include: linear discriminants, support vector machines, nearest neighbor classifiers, Hidden Markov Models and neural networks such as multi-layer perceptrons and self-organizing maps.

Table II gives an overview of several ECG classification approaches (this of course being far from an exhaustive list of the various approaches to ECG classification but it is still fairly representative of the different methods that have been to this problem), listing the employed features, the classification method, the sensitivity/accuracy of each approach, the beat types that were recognized from the system and finally whether the system was trained and tested using the entire MIT-BIH Arrhythmia database or just a fraction of it. It should be noted however that different research groups tend to use different sets of training and test data which vary in size and relative distribution. Also some authors choose to classify beats based on their MIT-BIH Arrhythmia database label while others employ the grouping of beats suggested by the Association for the Advancement of Medical Instrumentation (AAMI) [105].

The ECG classification approaches, which are listed in Table II, are not all suitable for resource constrained embedded wearable systems. Only the methods described in [97], [100] and [103] hold the promise for real-time operation, since they either utilize raw data samples as inputs to the classifier as in [100] where real-time operation on a smart-phone is demonstrated or they simply require projections on selected basis functions [97], [103].

The authors in [106] and [107] illustrate two different patient-adaptive ECG beat classification schemes which utilize both a global and a local classifier, whereby the first one is trained on a variety of ECG beats taken from several patients while the second one utilizes patient-specific beat classification results to enhance the accuracy of the system per individual. Llamendo et al [108], [109] recently investigated efficient feature selection strategies for ECG beat classification using the AAMI recommendations. By means of a sequential forward floating search algorithm they were able to identify a subset of temporal, morphological and statistical features that can greatly enhance the classification accuracy of a MLP classification model compared to previous works.

The final step in ECG analysis is rhythm classification. In normal ECG rhythms the electrical impulse originates in the sinoatrial node (SA), the heart's natural pacemaker. Abnormal heart rhythms are manifested when the impulses begin in a fast and irregular manner, and from various regions of the heart like the atria or the ventricles. Amongst these arrhythmias it is important to be able to differentiate between life-threatening ones (like Ventricular Flutter or Fibrillation) and other less risky arrhythmias (like Sinus Tachycardia). To accomplish this task, a series of consecutive ECG beats need to be examined in order to identify abnormal heart rhythms. Rodriguez et al [99] presented an accurate method for rhythm classification based on standard cardiologic rules and previous beat classifications. The resulting decision tree approach was able to identify abnormalities in heart rhythm with very high accuracy while also being able to run in real-time on a resource constrained device such as a personal digital assistant (PDA).

VI. Distributed Data Processing

The algorithms reviewed in Section V use a centralized architecture for making a decision. In the context of action recognition, when an unknown action occurs, all sensor nodes transmit their local results (e.g. extracted features) to a central node for the purpose of global classification. In contrast, in a distributed scenario, each node makes a local decision on the target action and may decide to propagate its local results to a next node. The amount of data transmitted over the network can be reduced to only a subset of the nodes that contribute to the classification of the movement. A distributed algorithm for action recognition needs a smaller number of the nodes to make a decision while maintains classification accuracy comparable to the centralized architecture [63]. Distributed processing offers better energy efficiency than centralized processing. Communication generally consumes more energy than local computation [110], [111]. From the energy preservation point it is a more beneficial to signal processing on individual nodes.

Several authors have investigated collaborative models for signal processing. Mostly, these algorithms have two major objectives: 1) to minimize number of active nodes that are involved in recognition of each action 2) to reduce amount of data that are exchanged among active nodes. These objectives can result in power-aware action recognition techniques that minimize the number of active nodes while the amount of communicated data is reduced. Two approaches on collaborative action recognition include *pseudo-dynamic node selection* and *dynamic node selection*. These optimization algorithms are centered around the concept of node selection. Node selection aims to select minimum number of nodes for classification. Pseudo-dynamic node selection introduced in [80] uses spatial primitives of the movements to construct a decision tree for classification. While a subset of the nodes is used to build the decision tree, classification takes different paths on the tree for detecting different actions. In dynamic node selection presented in [63], [112], active nodes are detected in real-time based on observations made by individual sensor nodes. This distributed classification model uses movement transcripts to reduce the amount of data that are being transmitted among the nodes. A more heuristic approach to dynamic node selection is presented in [113].

VII. Open Challenging Issues

There are many other challenges in the development of wireless medical embedded systems. These include the development of application-specific features to increase robustness and fault-tolerance; compression and security at the data level to secure communication and lower energy costs; energy reduction through communication optimization; and back-end data analytics. Finally, there are several challenges that apply to the community, such as developing publicly available test datasets for verifying claims and comparing algorithms and the need for a development platform aimed at the needs of the wireless health community.

A. Application-Specific Features

Initial work in wireless health relied on simple statistical features due to ease of calculation. However, more recently, other approaches have been used. A comparison of several feature types is presented in [114]. Moving forward, it will be important to develop features specific to particular applications or processing capacity [115]. By making features more relevant, a smaller number of features can be used for accurate pattern recognition. This will reduce computation and decrease the amount of training data required.

An example of the importance of application-specific features is sensor misplacement. For motion monitoring, sensor misplacement is an ever-present problem. Sensors may be placed on the wrong limbs, or at the right limbs but an incorrect position, or even upside down. This is inevitable in deployment, therefore algorithms will need to account for this. One approach is to find signals/features that are insensitive to node misplacement, and use them for classification [116]. Another technique builds a statistical model of misplacement, which approximates errors based on experimental data [117]. In other work, genetic programming is used to extract and compose features robust to sensor misplacement [51].

B. Compression and Security

At the data and communication level, compression and security will both play very large roles in any commercial deployment. Compression reduces transmission bandwidth, and thus conserves energy. Encryption and authentication protocols can prevent snooping and data injection.

Compression can be lossless or lossy, and application-aware or application-agnostic. In one system, researchers developed a lossless compression co-processor which uses very little energy compared to the processor [118]. Lossy compression can be applied to signals with known characteristics without sacrificing important information. For example, compression on ECG signals using wavelets [119].

As wireless health platforms become more attractive for medical applications, it will become necessary to develop communication protocols that are robust to interference and secure from snooping and data injection. The biggest challenge for encryption is that attackers potentially have access to laptop-level processing power, while the encryption tasks must share the already constrained on-node processor with the signal-processing tasks. Tan, *et al* propose a system based on public key cryptography. New keys are generated in advance covering small segments of time to grant access to specific individuals only for small periods of time [120]. It is also possible to generate a key using biometric data sensed from the body to contribute to the generation [121]–[123].

C. Datasets

One considerable impediment to signal processing and pattern recognition design on wireless health is the lack of good publicly available and standardized datasets. Without such datasets it is difficult to compare the accuracy of recognition algorithms. The imaging processing community has a standard set of images for comparing processing techniques [124], the ECG analysis community has several large databases of ECG data, and the BCI community has a set of brain recordings. As of yet, there is no standard in this community, which makes it harder to verify claims and compare algorithms. Correcting this problem should be a priority of the community.

D. Development Platform

Another necessary component is a platform for development, training, and simulation. There are several platforms available for Wireless Sensor Networks, such as TinyOS [125]. However, Body Sensor Networks have specific needs and constraints. For instance, most body sensor networks are deployed in a star topology with a powerful base station node. Further, there is a really high emphasis on pattern recognition. A typical design and training is to set recognition goals, pick sensor locations and capabilities, build the software, and train the signal processing.

One platform that addresses the specific needs of wearable monitoring systems is Signal Processing in Node Environment (SPINE) [126]. It is a lightweight API built on top of TinyOS on the sensor node side and Java on the base station side. It provides support for sensor discovery, radio protocol selection, and basic signal processing. It is extensible through custom programming [127], [128].

The Health Integration Platform (HIP) is another platform aimed at this area written in Java [129]. HIP has a more flexible architecture and supports modular analysis, as well as supporting more mote operating systems and types. However, it appears to be aimed more at data collection scenarios rather than pattern recognition, and at this time offers no support for design-side activities such as training and automated sensor placement.

VIII. Conclusion

As we move further into the 21st century, affordability of healthcare is becoming a bigger and bigger issue. As with other fields, greater automation is the key to reducing costs. Wireless medical embedded systems offer this automation through ubiquitous patient monitoring and automated data analysis and event sensing. As many medical applications rely heavily on pattern recognition and signal processing, the development of lightweight and distributed signal processing has been crucial to this field. In this paper, we presented a pipeline model which encompasses many of these algorithms and techniques in literature.

Moving forward, developments in signal processing will continue to be critical to the success of body sensor networks. As with many signal processing fields, we believe that the development of application specific features is critical, while the recognition algorithms themselves will be generic and applicable across a wide range of applications. Furthermore, tools and frameworks are required to build applications across heterogeneous sensor systems and at various levels of computation. The tools will need to be able to train pattern recognition tools from available test data, potentially convert existing training data to match new sensors, and handle node placement. Moreover, once different components of the system are designed (including signal processing modules), an optimization of the entire system is required to ensure feasibility of hardware, software, and signal processing blocks for real-world deployment. Optimization can be done within each and every component of the system; however, there would be tradeoffs for choosing optimum configuration. This is mainly due to the fact that the components are interoperable and do not function independent of each other. For example, while a per-node data reduction can reduce the amount of data that is being transmitted across the networks, it may cause reduction in the recognition accuracy of the system.

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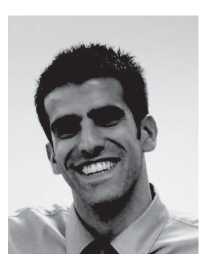

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