Non-Invasive Measurement of Heartbeat with a Hydraulic Bed Sensor

Progress, Challenges, and Opportunities

David Heise
Dept. of Computer Science, Technology & Mathematics
Lincoln University
Jefferson City, Missouri, USA
HeiseD@lincolnu.edu

Licet Rosales, Mary Sheahen, Bo-Yu Su, Marjorie Skubic
Center for Eldercare and Rehabilitation Technology
University of Missouri
Columbia, Missouri, USA
{lr5zf, misq4f, bsdg6}@mail.missouri.edu, SkubicM@missouri.edu

***Abstract*—A hydraulic bed sensor has been developed to non-invasively measure heartbeat during sleep. The motivation for this work is to enable early detection of physiological and behavioral change, thereby allowing effective interventions prior to an acute event. The transducer configuration and signal processing strategies have progressed to provide a low-cost, effective solution to eldercare monitoring needs. This sensor is now being deployed into the homes of elders in two locations, integrating into existing ambient sensor networks to generate clinician alerts and provide an improved quality of care. Challenges and opportunities remain, and this paper reports on the current progress and development of the system.**

Keywords—hydraulic bed sensor; eldercare monitoring; ballistocardiography

I. INTRODUCTION

Demand for a low-cost, robust instrument for capturing physiological parameters during sleep is high and growing. Eldercare monitoring, in the home, is perhaps the most prominent venue for this technology. Research has shown that long-term monitoring of elders in the home may lead to potential interventions that will contribute to maintaining health, quality-of-life, and independence [1]. Deploying sensor networks that can capture data from the environment is a leading approach toward implementing this strategy, but an essential element to widespread adoption of sensors in the home is a requirement that the sensors not affect the comfort or lifestyle of the person being monitored. Bed sensors hold great promise as a key component of these sensor networks, and sensors employing ballistocardiography are emerging as a favored option for capturing desired physiological data [2].

Ballistocardiography is perfectly suited to this purpose. As the ballistocardiogram (BCG) signal results from the natural forces associated with the ejection of blood from the heart at each contraction, there is no special activity or protocol for a subject to perform. Additionally, this signal is readily (in fact, most readily) captured when the body is at rest. The seminal research in this area was completed by Starr [3], but advances in technology now allow development of innovative devices that are less expensive, easier to deploy, and more sensitive [4].

The hydraulic bed sensor developed by the author [5] is one such device. This device is positioned beneath the mattress to provide sensing without any effect on subject comfort; in fact, the subject cannot even notice the device is deployed. The Center for Eldercare and Rehabilitation Technology (CERT) at the University of Missouri has continued development of the device to a multi-transducer arrangement [6] (see Fig. 1). This new arrangement allows for more reliable capture of the BCG signal, as the transmission of forces from the body to the transducer depend somewhat on position of the body on the mattress, and on the orientation of the body relative to the transducer below. Through analysis and fusion of the four transducer signals, it is possible to select both the transducer providing the best signal-to-noise ratio (SNR) and the location of the body on the mattress.

Based upon the success and cost-effectiveness of this sensor arrangement, CERT has now deployed the sensor into the homes of seniors in two aging-in-place communities: TigerPlace, in Columbia, MO, and Western Home Communities, in Cedar Falls, IA. In this paper, we report initial findings while we continue to collect data from our study population.

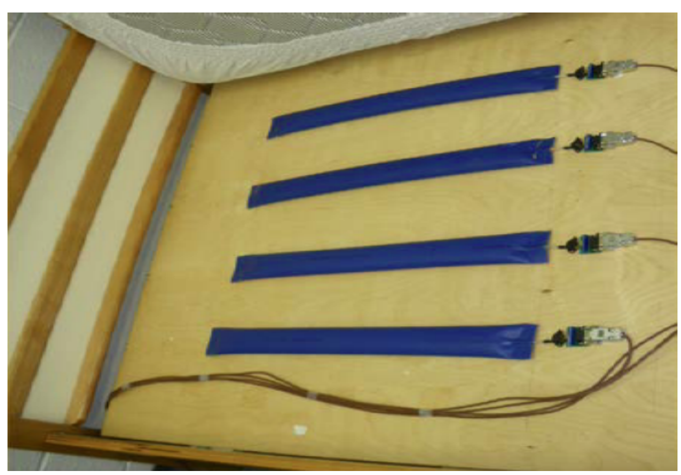

Figure 1. Hydraulic bed sensor multi-transducer configuration.

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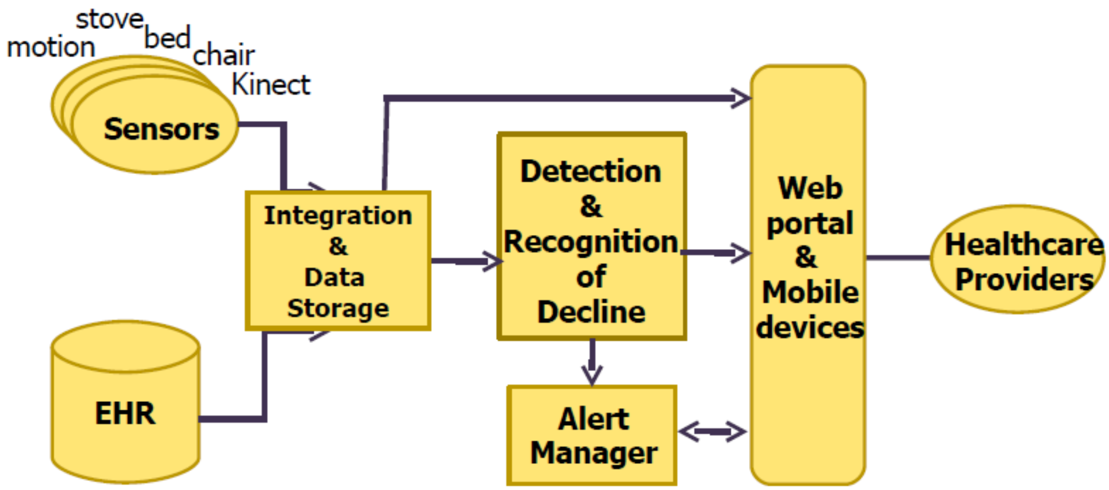

Figure 2. System architecture for deployed sensor networks.

II. System Architecture and Environmental Setup

Over the past decade, CERT has deployed sensor networks and collected data from 65 homes of seniors in two locations. These sensor networks include motion sensors, bed sensors, gait analysis systems, and other devices in varying stages of development (e.g., fall detectors). The basic architecture is outlined in Fig. 2. Various sensing modalities are used to collect data via a logger (dedicated PC) discreetly placed within each residence. The local data logger connects to a central server, which serves as a repository for all of the collected data from all of the monitored population. A number of algorithms are run on this collected data, looking for abnormalities or other patterns that may trigger alerts to caregivers, potentially prompting a visit or other attention to a resident. Collected data is available to healthcare providers via a convenient web interface, allowing review in response to an alert or other reason for inquiry.

III. Algorithm Selection and Opportunities

The CERT team has developed and tested a set of algorithms for processing the hydraulic bed sensor BCG signals that each have particular strengths, and research is underway to determine how best to fuse the results from the separate algorithms, perhaps even applying different algorithms to each of the concurrently collected transducer signals to achieve the most accurate and robust result. Three algorithms currently being used or in development are described below.

A. Windowed Peak-to-Peak Deviation Algorithm

The Windowed Peak-to-Peak Deviation (WPPD) algorithm, first described in [5], then improved and clarified in [7], may be compared to detecting the amplitude modulation of the signal acquired through the hydraulic signal. This approach does not rely upon an (improper) assumption of stationarity in the BCG signal. Additionally, it is reasonably robust to noise caused by the integrated piezoresistive pressure sensor as well as the system through which the BCG is transmitted (i.e., small body movements, oscillation of the mattress, environmental vibration). The method suffers two primary drawbacks: 1) the exact time-location of each heartbeat is skewed, making estimates of beat-to-beat intervals less accurate, and 2) optimizing the method requires some tuning of parameters, and while automatic adaptation of parameter to a particular subject is likely possible, this problem is not yet solved.

B. Clustering Approach to Heartbeat Detection

A clustering approach to heartbeat detection was developed in [6], based on prior work by Brueser [8, 9]. This method attempts to detect the J-peak of each heartbeat in the BCG waveform, based upon features derived from the waveform itself. An advantage of this approach is that time-locations of reported heartbeats are quite accurate. Like the WPPD algorithm, this approach is also not reliant upon a stationary signal. There appears to be some difficulty, though, in detecting false J-peaks or missing heartbeats for some subjects. Work is continuing to refine this method and employ additional features and constraints to yield more reliable results across a spectrum of subjects.

C. Hilbert Transform Algorithm

Su [10] has reported improved heart rate detection from the BCG signal over the methods described above. This approach uses the Hilbert transform to extract pulse envelopes from the filtered and windowed BCG signal, followed by an fast Fourier transform (FFT) to extract frequency content, yielding the pulse rate of the signal. Indeed, results are impressive when the BCG signal is relatively stationary, but this also represents the primary limitation of this approach. While heartbeats can be, and often are, relatively stationary for long periods of time, capturing heart rate and heart rate variability (including beat-to-beat intervals) is equally if not more important when the heartbeats are not uniform in time, or when heart rate changes quickly.

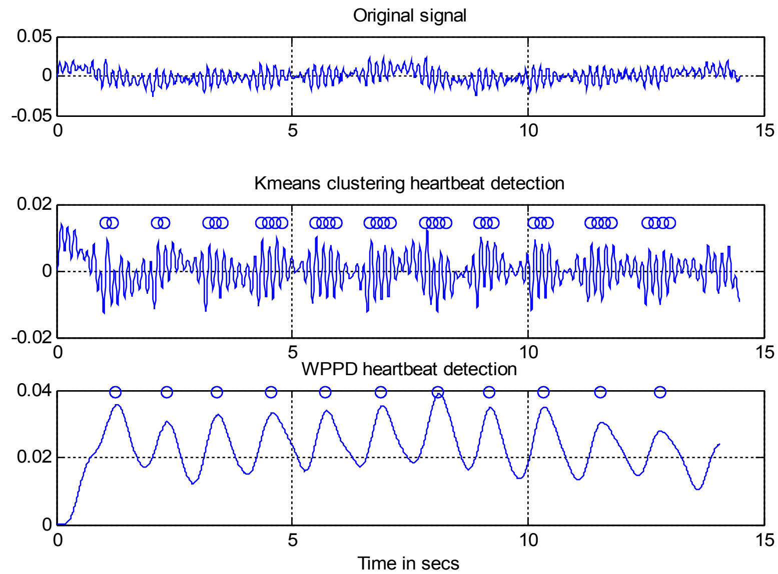

Figure 3. Example of the WPPD algorithm performing better than the clustering algorithm. At top, the original (time domain) signal; middle, the K-means clustering result; and bottom, the WPPD result. The circles above the signals indicate where heartbeats were detected. The y-axis represents amplitude (volts), but due to algorithm processing the scale of each graph cannot be directly compared.

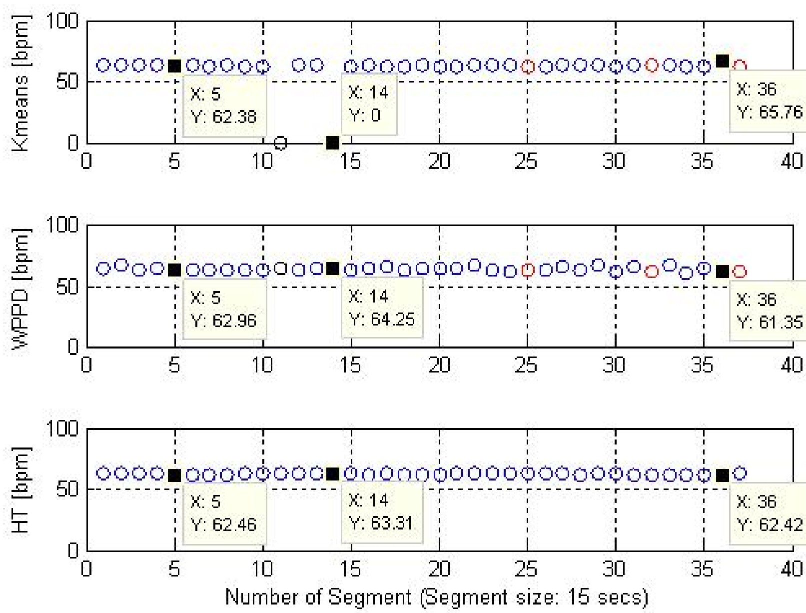

Figure 4. Results of all three algorithms performing on a given signal. The original signal is divided into 15-second segments for algorithm processing, and the results are reported in beats per minute. Selected segments are highlighted to show exact heart rates reported by each algorithm at three separate times; X represents the (15-second) segment number from the signal shown, Y represents the reported heart rate in beats per minute.

D. Algorithm Opportunities

A number of opportunities and choices exist with regard to the above described algorithms. It should be noted that each of these algorithms have room for continued development, and thus none of them should be discounted out-of-hand. Each of the algorithms have been shown to perform very well in certain circumstances, and those strengths can be leveraged through parallel deployment of the algorithms and fusion of the results. Fig. 3 gives one example where the WPPD algorithm performs better than the clustering algorithm; Fig. 4 gives an example where all three algorithms perform competitively. This gives motivation for the conceptual fusion of the algorithms presented in Fig. 5. We do not, however, rule out other fusion approaches, such as crisp selection based on an expert decision system, or selection based upon a fuzzy rule set.

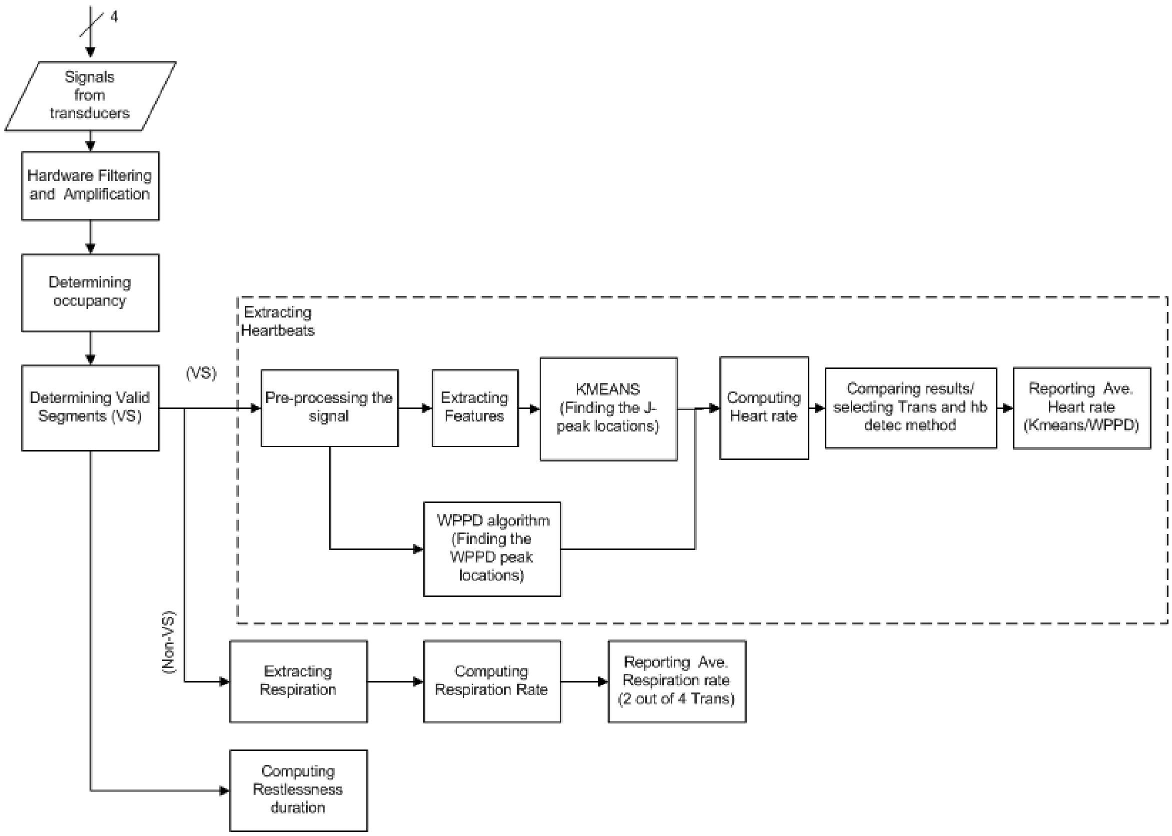

Figure 5. Block diagram for processing BCG signal from hydraulic bed sensor. This represents one of many possible algorithm fusion options.

Metrics to evaluate the confidence of the detection of a particular heartbeat are under development. One such approach is to evaluate the consistency of the inter-beat distances detected over a particular analysis segment (e.g., 15-second window). Generally speaking, we expect that inter-beat distances, and thus heart rate, will remain relatively constant. Working under this assumption, if we detect a very high variance in the inter-beat distances, our confidence of correct identification of individual heartbeats is lower. This confidence may contribute to a choice of particular algorithm or algorithm parameters, and may also be used (as suggested in the next section) to select the best transducer from the four elements comprising the bed sensor.

IV. Transducer Selection and Signal Fusion

The transducer configuration provides a plethora of options for signal analysis (for one example, see Fig. 5). Research is underway to determine how best to fuse the results from the separate algorithms, perhaps even applying different algorithms to each of the concurrently collected transducer signals to achieve the most accurate and robust result.

A. Transducer Selection

As with algorithm selection, transducer selection provides a number of choices. At present, we employ some strategies to select the "best" transducer. A very straightforward approach is to examine the DC bias present on each of the transducer signals and select the transducer with the highest DC bias. This approach makes the assumption that: a) the transducer with the highest DC bias will be the one over which the body is most directly positioned, and b) the transducer directly beneath the body will generally provide the best signal. We have found, however, this this assumption does not consistently hold, and is also susceptible to variations in the manufacture of the transducer elements. An improved approach, applicable to the Hilbert transform algorithm, is to analyze the four parallel signals in the frequency domain and select the signal with the most prominent peak; this implies the "clearest" signal to the algorithm. Yet another approach is to examine the inter-beat distances that are reported from the algorithm for each of the transducer signals. Using a 3-class K-means clustering of the reported inter-beat distances, then examining the percentage of heartbeats assigned to the largest cluster, we are able to calculate a confidence for each of the four transducers. The rationale for this approach is that the inter-beat distance will tend to remain relatively constant, thus transducer signals with a lower SNR will yield more varied (and error-prone) reported inter-beat distances.

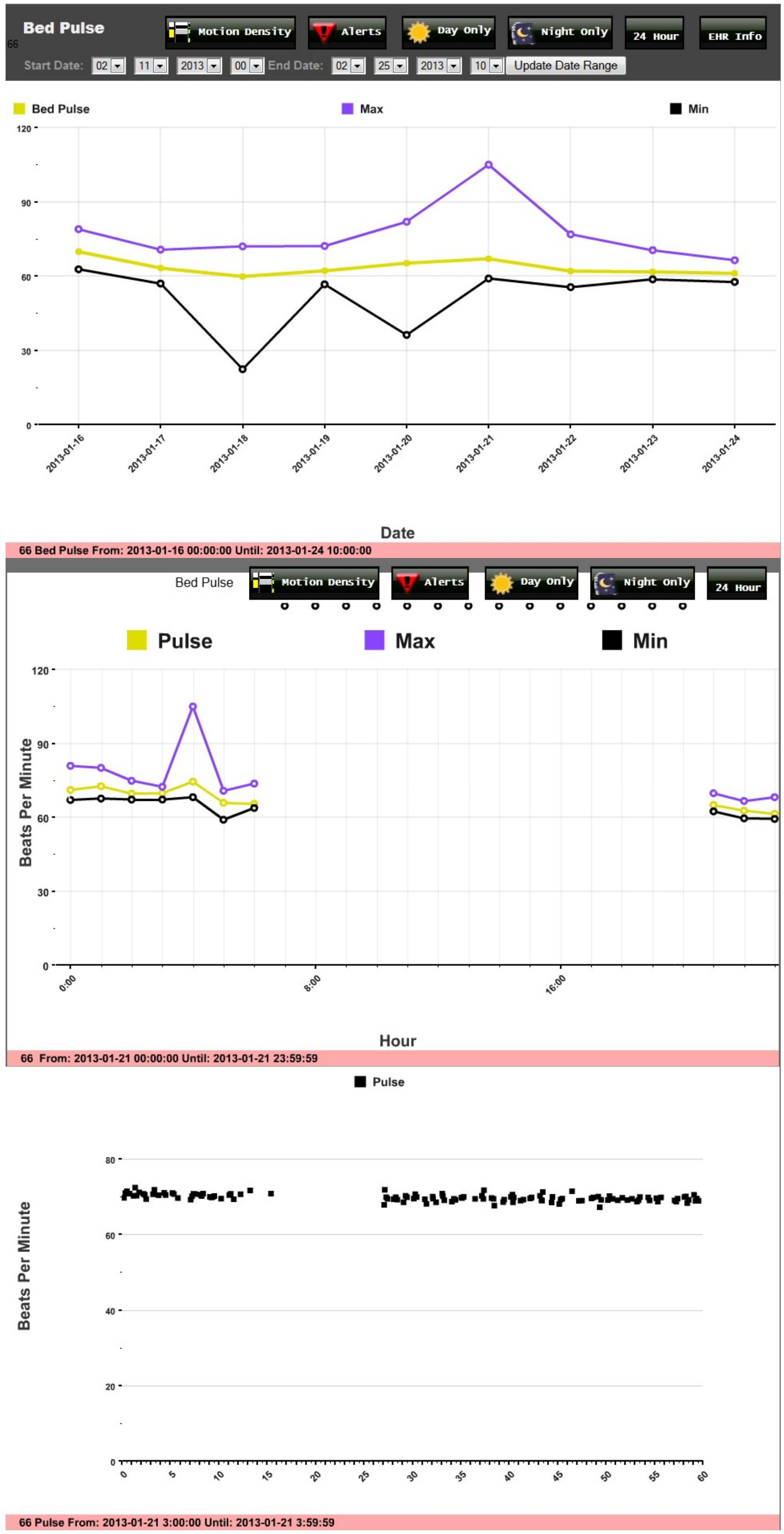

Figure 6. Sample output displays for clinician use, from actual data. The top figure shows the maximum, average, and minimum heart rates detected by day over a selected date range for a particular subject; the middle figure shows the maximum, average, and minimum heart rates detected by hour within a selected day; the bottom figure shows the specific heart rate calculated per 15-second segment within a selected hour. Gaps in the graphs represent times when a pulse rate was not computed, likely because the subject was not in bed.

B. Signal Fusion

An alternative to signal selection is to utilize the redundancy across transducers to ultimately provide a fused signal with a higher SNR that any of the individual transducers. Some useful, correlating data may be merged between multiple transducers, potentially increasing the SNR. Another possible outcome of signal fusion is to give a more reliable confidence of algorithm results by running the algorithms on multiple signals in parallel, perhaps including a fused signal as well. A further benefit of this approach is to detect possible conditions that may indicate a hardware failure or degraded performance from one of the four transducers. In fact, this has already yielded diagnostic information regarding a faulty transducer in our current sensor deployments.

V. Displaying the Results

As we collect more data, and increasingly complex data (including multiple, possibly redundant, signals containing the same physiological information), we must develop effective ways to present the data in a manner that is both clinically relevant and useful. In researching and developing the technology that is capable of providing better and more reliable information, it is imperative that consideration be given to the design of the user interface. CERT exemplifies the best of interdisciplinary research teams, as CERT includes not only engineers, but also clinicians and other direct users of the technology. Through regular and effective consultation with clinicians on our team, an interface is under development that meets the following goals:

1. Display average heart rate, restlessness, and respiration over several levels of time (average by day, average by hour, "raw" calculation per 15-second window) in a clinically meaningful way.
2. Display accurate time in bed levels using the sensor's determination of bed occupancy.
3. Display enough information to understand which data being collected is meaningful in order to both understand the results and to be able to improve on future displays, and to do this without overloading the user with too much information.

Fig. 6 provides an example of the interactive nature of the prototype web interface. The top image displays heart rate for a subject over a nine-day period, showing maximum, average, and minimum values for each day in the specified range. The user may then select a data point on a particular day to zoom into an hour-by-hour graph for the same subject (middle image). The user can zoom-in even further by selecting a data point, at which time a graph is displayed in a line chart showing the pulse rate calculated at each 15-second interval during the hour of interest (bottom image).

VI. Moving Forward

As mentioned in the introduction, CERT has deployed the current hydraulic bed sensor (4-transducer configuration) into homes of elders at TigerPlace in Columbia, MO, as well as in Western Home Communities in Cedar Falls, IA. These sensors are being configured to merge seamlessly with our sensor networks, using the same infrastructure to transmit data to CERT loggers and servers for generating clinician alerts and enabling trend analysis [1]. In this manner, CERT is moving ever closer to closing the monitoring loop; that is, developing the technology that is able to detect the changes in elders that may lead to proactive interventions [11]. We are presently collecting a significant pool of data from our target population, in their normal environment, versus controlled experiments in our laboratory setting. This is another important step forward in the continuing development and improvement of the hydraulic bed sensor, and toward improved measurement of important physiological parameters during sleep.

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