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# Tracking Clinical Status for Heart Failure Patients using Ballistocardiography and Electrocardiography Signal Features

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## Abstract

Heart failure (HF) is an escalating public health problem, with few effective methods for home monitoring. In HF management, the important clinical factors to monitor include symptoms, fluid status, cardiac output, and blood pressure – based on these factors, inotrope and diuretic dosages are adjusted day-by-day to control the disorder and improve the patient's status towards a successful discharge. Previously, the ballistocardiogram (BCG) measured on a weighing scale has been shown to be capable of detecting changes in cardiac output and contractility for healthy

subjects. In this study, we investigated whether the BCG and electrocardiogram (ECG) signals measured on a wireless modified scale could accurately track the clinical status of HF patients during their hospital stay. Using logistic regression, we found that the root-mean-square (RMS) power of the BCG provided a good fit for clinical status, as determined based on clinical measurements and symptoms, for the 85 patient days studied from 10 patients ($p < 0.01$). These results provide a promising foundation for future studies aimed at using the BCG / ECG scale at home to track HF patient status remotely.

## I. Introduction

Despite advances in treatment and relative improvement in survival, the rate of heart failure (HF) hospitalizations has surpassed one million yearly, with HF becoming the leading hospital diagnosis for Medicare patients [1, 2]. Of the $30B per year in HF related health care costs [3], 70% are due to hospitalizations – this represents an increase of 155% in the past two decades [4]. HF is the leading cause of hospitalization for elderly patients, and the most recent estimates of HF readmission rates to the hospital after a discharge for HF are 25% after 30 days, and 45% after 6 months [5–7]. This rapid time-to-readmission, often faster than the next scheduled physician visit, has necessitated the development of home monitoring solutions, ranging from phone calls from a nurse [8] to implantable hemodynamic monitoring devices [9].

The most commonly used home monitoring solution for HF is daily bodyweight monitoring. In 2007, Chaudhry, et al. found that changes in bodyweight measured daily were associated with HF hospitalizations, and significant changes in weight preceded admission by one week [10]. However, recently, Chaudhry, et al. ran a large randomized control trial with 1653 patients in an attempt to reduce readmission rates using daily weight measurement and telemonitoring – unfortunately, the results showed no improvement in readmission rates or mortality [11]. Furthermore, body weight monitoring is not reliable over longer periods of time since bodyweight can change for a number of other reasons [12, 13].

In addition to body weight measurements, hemodynamic monitoring at home could provide a more specific and sensitive means of monitoring HF patient status, with the potential to reduce rehospitalization rates while improving the overall quality of care. Recently, ballistocardiogram (BCG) measurements on a weighing scale have been demonstrated by two of the authors of this paper in previous work at Stanford University, and others, as a means of measuring changes in cardiac output [14], contractility [15], and beat-by-beat left ventricular function during arrhythmias [16]. The BCG is a measure of the reaction forces of the body in response to the heartbeat, and can be measured by the weighing scale as small fluctuations in bodyweight associated with displacements of the body center of mass. Furthermore, initial BCG studies with HF patients in clinic demonstrated that the morphological consistency of the BCG signal from one heartbeat to the next might be indicative of a patient's clinical status [17].

In this study, a multi-disciplinary collaborative effort between engineers and cardiologists, we planned to explore the capability of longitudinal BCG and electrocardiogram (ECG) measurements taken on a wireless modified weighing scale to classify the changes in clinical

status of HF patients. Specifically, we aimed to address the question: Can changes in the root-mean-square (rms) power of the BCG – a feature previously found to be correlated to changes in cardiac output [14] – be used to classify whether clinical status improved or did not improve from one day to the next? This work would then provide the foundation for future studies using the BCG / ECG measurement hardware at home, aimed at creating predictive models for worsening or improving status for HF patients. A block diagram illustrating this work in the context of our previous efforts, and those previously published in the existing literature is shown in Figure 1.

## II. Methods

### A. Subject Population

This study was conducted under a protocol reviewed and approved by the University of California, San Francisco (UCSF) and Georgia Institute of Technology (GT) Institutional Review Boards (IRBs). All subjects provided written informed consent before experimentation.

Ten subjects with HF participated in the study, where BCG and ECG measurements were taken periodically (approximately once every day or every two days) throughout their treatment in the clinic. A total of 85 patient days were studied from these subjects. In addition to BCG and ECG recordings, the inotrope and diuretic dosage, fluid status (in and out), blood pressure, and symptoms were recorded or obtained from the patient's medical record.

### B. Hardware and Software

The BCG and ECG signals were measured as previously described [18], with the strain gauges and handlebar electrodes from the scale being interfaced to custom electronics. In this implementation, a microcontroller and Bluetooth radio were also used to send the signals wirelessly to a laptop for storage. The BCG signals were sampled at 120 Hz and the ECG at 1 kHz. All BCG and ECG recordings were administered by clinical personnel – nurses, medical students, or study coordinators – not engineering team members. The personnel simply instructed the subjects to remain as still as possible while on the scale.

A computer application was designed and implemented in C#, allowing for the real-time visualization of the data and facilitating the connection of the device to the laptop via Bluetooth SPP. The data were stored in comma-separated-values (CSV) format on the laptop.

### C. Data Analysis

**1) Clinical Score—**The clinical status of the patients from one day to the next was quantified by combining different aspects of patient health that are most relevant to HF management. Specifically, based on the patient's diuretic and inotrope dosages (*DD* and *ID*), symptoms (*Sx*), and blood pressure (*BP*), a clinical score (*CS*) was derived to determine if the patient's condition improved, or did not improve, from one day to the next. For each attribute, if the patient improved compared to the previous day, a value of +1 was given; if

remained the same, 0; if worsened, −1. For example, if on day *k* the patient developed shortness of breath compared to the previous day, then $Sx_k = -1$; if a different patient's diuretic dosage decreased on day *k* compared to the previous (indicating improved condition), then $DD_k = +1$. The clinical score was calculated as an average of these four attributes as follows:

$$CS_k = \frac{DD_k + ID_k + Sx_k + BP_k}{4} \quad (1)$$

As a result, the composite clinical score could take on values ranging from −1 to +1. Similar methods for developing a clinical score for quantifying HF patient status have been proposed in the existing literature by Packer [19].

**2) BCG and ECG Signal Processing—**The BCG and ECG signals were processed using Matlab® to reduce measurement noise, extract features of interest automatically, and use logistic regression to quantify the goodness-of-fit for the rms power of the BCG to the composite clinical score. The pre-processing of the BCG and ECG signals were as described in previous work [16, 18]; briefly, the signals were band-pass filtered to reduce out-of-band noise, the ECG R-waves were used as a trigger for ensemble averaging the BCG heartbeats (20–30 beats used per subject), and rms power was computed for each ensemble averaged BCG beat. One ensemble averaged BCG beat was computed for *k*th day's recording for a patient, and the rms power was calculated for this beat ($BCG_{rms,k}$). Since the clinical score measures changes in status from one day to the next, a similar relative measure was created for the BCG rms power for one day versus the previous day, as simply the difference $\Delta BCG_{rms,k} = BCG_{rms,k} - BCG_{rms,k-1}$.

**3) Statistical Analysis—**Logistic regression was used with $\boldsymbol{\Delta BCG_{rms}}$ as the feature vector, and ***CS*** as the target vector to determine the goodness-of-fit, and area under the receiver operating characteristic (ROC) curve (AUC). The level of statistical significance was set at $p < 0.05$. The fit of BCG rms power to each attribute within the clinical score (DD, ID, Sx, BP) was also investigated and the same criteria were used for evaluating significance.

## III. Results

### A. Example Results for One Subject

Figure 2 shows $BCG_{rms}$ measurements for one subject over time, alongside the clinically relevant "events". The subject was admitted for management of cardiac amyloidosis, and the condition worsened to the point of receiving a heart transplant on hospital day 37. Each time the subject had a negative clinically relevant "event," such as an infection, the BCG rms power decreased on or near that day. In the days leading up to the heart transplant, the subject's condition was poor, and the BCG rms power was consistently low. Following the heart transplant, the rms power increased substantially. Each event produced a corresponding change in the BCG signal that was consistent with the clinical course.

Figure 3 shows ensemble averaged BCG waveforms before and after the heart transplant. Following transplant, the BCG signal amplitude and rms power increase substantially (0.21 to 0.40) indicating an increase in cardiac output. The BCG R-J interval increased by 13 ms following the transplant, reflecting the decreased inotrope dosage, as inotropes are no longer required for the donor heart.

### B. Statistical Results for All Subjects

Changes in the BCG rms power were found to be a good fit for the clinical score ($p < 0.01$, AUC = 0.68, Se = 0.62, Sp = 0.62). The direction of the fit was as expected physiologically, with increasing BCG rms power indicating a likelihood of improving clinical score. Among the attributes, the BCG rms power was found to best fit *DD*, *ID*, and *Sx* ($p < 0.05$), and trended such that increasing BCG rms power indicated improvement in all of these attributes (e.g. less reported symptoms and decreased *ID* and *DD*).

## IV. Discussion, Limitations, and Future Work

The results support our hypothesis that the BCG rms power changes on a day-by-day basis can be used to model the clinical status changes using logistic regression techniques. This further reinforces the importance of the BCG rms power as a feature relevant to monitoring HF patient status with BCG signals.

One limitation of this study was that 45 of the 85 patient days were derived from one subject. In future work, we plan to expand the datasets from the other subjects as well to provide better balance in the overall results. Additionally, other features from the BCG will be considered, such as the frequency domain features and time intervals. Furthermore, it is important to note that this approach would detect *changes* in clinical status, not the clinical status itself.

It should also be noted that this study was conducted in the clinic, not at home; consequently, the degree of changes in clinical status from one day to the next were, aside from major events, relatively small. The purpose of the treatment is to improve the patient's status gradually with interventions until discharge. We anticipate that at home, the changes in clinical status over time will be much more drastic than in the clinic, as a person will change from feeling well at discharge, to decompensation upon the next admission to the emergency room or clinic. Consequently, for these larger changes, the BCG should provide stronger ability to track clinical status.

In future studies, where BCG and ECG equipped weighing scales will be provided to HF patients after discharge, we plan to use more sophisticated machine learning algorithms to predict worsening status in advance. This type of technology would not only allow physicians to adjust diuretic dosages remotely, but would also empower patients, giving them a tool for self-monitoring and the ability to take control over their therapy. Eventually, graded action plans similar to those established for asthma control, could be constructed for optimal titration of medication and improved quality of life.

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## References

1. Huffman MD, Berry JD, Ning H, Dyer AR, Garside DB, Cai X, et al. Lifetime Risk for Heart Failure Among White and Black AmericansCardiovascular Lifetime Risk Pooling Project. Journal of the American College of Cardiology. 2013; 61:1510–1517. [PubMed: 23500287]
2. Go AS, Mozaffarian D, Roger VL, Benjamin EJ, Berry JD, Borden WB, et al. Heart Disease and Stroke Statistics 2013 Update: A Report From the American Heart Association. Circulation. Jan 1.2013 127:e6–e245. [PubMed: 23239837]
3. Heidenreich PA, Albert NM, Allen LA, Bluemke DA, Butler J, Fonarow GC, et al. Forecasting the Impact of Heart Failure in the United States: A Policy Statement From the American Heart Association. Circulation: Heart Failure. May 1.2013 6:606–619. [PubMed: 23616602]
4. Roger VL, Weston SA, Redfield MM, et al. Trends in heart failure incidence and survival in a community-based population. JAMA. 2004; 292:344–350. [PubMed: 15265849]
5. Keenan PS, Normand S-LT, Lin Z, Drye EE, Bhat KR, Ross JS, et al. An Administrative Claims Measure Suitable for Profiling Hospital Performance on the Basis of 30-Day All-Cause Readmission Rates Among Patients With Heart Failure. Circulation: Cardiovascular Quality and Outcomes. Sep 1.2008 1:29–37. [PubMed: 20031785]
6. Jencks SF, Williams MV, Coleman EA. Rehospitalizations among Patients in the Medicare Fee-for-Service Program. New England Journal of Medicine. 2009; 360:1418–1428. [PubMed: 19339721]
7. Krumholz HM, Parent EM, Tu N, et al. Readmission after hospitalization for congestive heart failure among medicare beneficiaries. Archives of Internal Medicine. 1997; 157:99–104. [PubMed: 8996046]
8. Giordano A, Scalvini S, Zanelli E, Corrà U, LGL, Ricci VA, et al. Multicenter randomised trial on home-based telemanagement to prevent hospital readmission of patients with chronic heart failure. International Journal of Cardiology. Jan 9.2009 131:192–199. [PubMed: 18222552]
9. Bui AL, Fonarow GC. Home Monitoring for Heart Failure Management. Journal of the American College of Cardiology. 2012; 59:97–104. [PubMed: 22222071]
10. Chaudhry SI, Wang Y, Concato J, Gill TM, Krumholz HM. Patterns of Weight Change Preceding Hospitalization for Heart Failure. Circulation. Oct 2.2007 116:1549–1554. [PubMed: 17846286]
11. Chaudhry SI, Mattera JA, Curtis JP, Spertus JA, Herrin J, Lin Z, et al. Telemonitoring in Patients with Heart Failure. New England Journal of Medicine. 2010; 363:2301–2309. [PubMed: 21080835]
12. Wolfel EE. Can We Predict and Prevent the Onset of Acute Decompensated Heart Failure? Circulation. Oct 2.2007 116:1526–1529. [PubMed: 17909113]
13. Anker SD, Negassa A, Coats AJS, Afzal R, Poole-Wilson PA, Cohn JN, et al. Prognostic importance of weight loss in chronic heart failure and the effect of treatment with angiotensin-converting-enzyme inhibitors: an observational study. The Lancet. Mar 29.2003 361:1077–1083.
14. Inan OT, Etemadi M, Paloma A, Giovangrandi L, Kovacs GTA. Non-invasive cardiac output trending during exercise recovery on a bathroom-scale-based ballistocardiograph. Physiological Measurement. 2009; 30:261. [PubMed: 19202234]
15. Etemadi M, Inan OT, Giovangrandi L, Kovacs GTA. Rapid Assessment of Cardiac Contractility on a Home Bathroom Scale. Information Technology in Biomedicine, IEEE Transactions on. 2011; 15:864–869.
16. Inan OT, Etemadi M, Wiard RM, Giovangrandi L, Kovacs GTA. Robust ballistocardiogram acquisition for home monitoring. Physiological Measurement. 2009; 30:169. [PubMed: 19147897]

17. Giovangrandi L, Inan OT, Banerjee D, Kovacs GTA. Preliminary results from BCG and ECG measurements in the heart failure clinic. Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE. 2012:3780–3783.

18. Inan OT, Dookun P, Giovangrandi L, Kovacs GTA. Noninvasive Measurement of Physiological Signals on a Modified Home Bathroom Scale. Biomedical Engineering, IEEE Transactions on. 2012; 59:2137–2143.

19. Packer M. Proposal for a new clinical end point to evaluate the efficacy of drugs and devices in the treatment of chronic heart failure. Journal of Cardiac Failure. 2001; 7:176–182. [PubMed: 11420770]

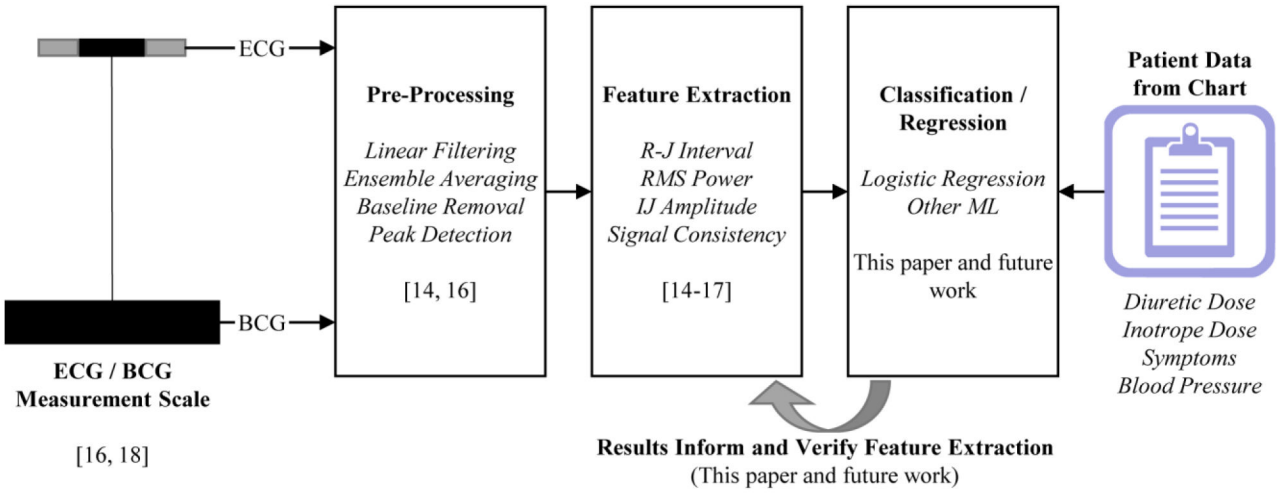


**Figure 1.**

Block diagram showing system components – hardware, software, clinical data – required for advancing BCG based HF monitoring research. Previously completed and published work is referenced for each of the blocks. This paper presents results from a study aimed at investigating logistic regression as a tool for fitting BCG rms power to clinical status for HF patients in the clinic.

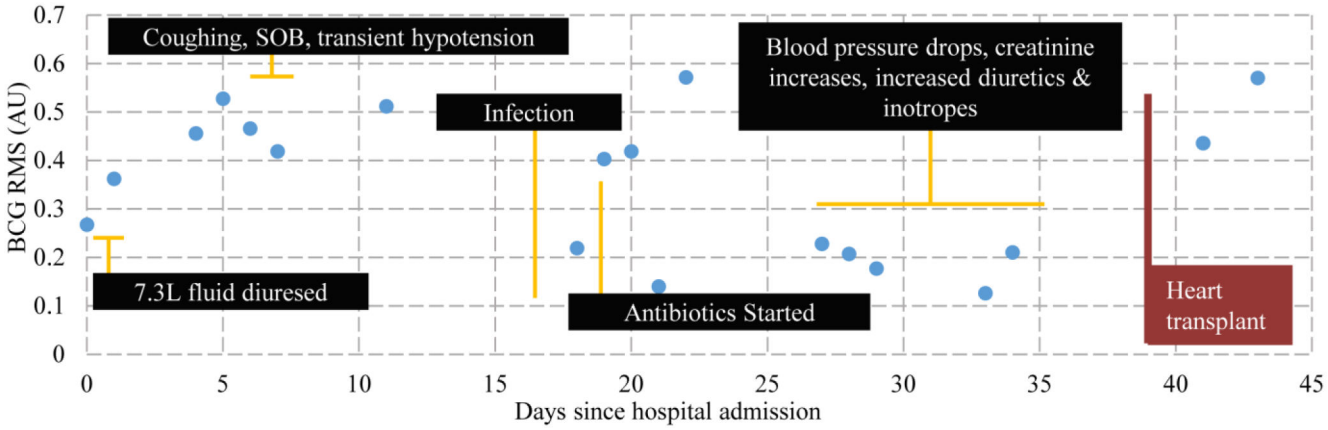


**Figure 2.**

BCG rms power (in arbitrary units) and clinical events recorded during an HF patient's treatment in the hospital (note that some clinical events occurred in between BCG measurements). Each positive event (antibiotics, heart transplant) lead to an increase in the BCG rms power, and each negative event (transient hypotension, infection, increased creatinine) lead to a decrease in BCG rms power. Note the worsening overall trend in BCG rms power until day 37, when the patient had a heart transplant and the BCG rms power increased substantially.

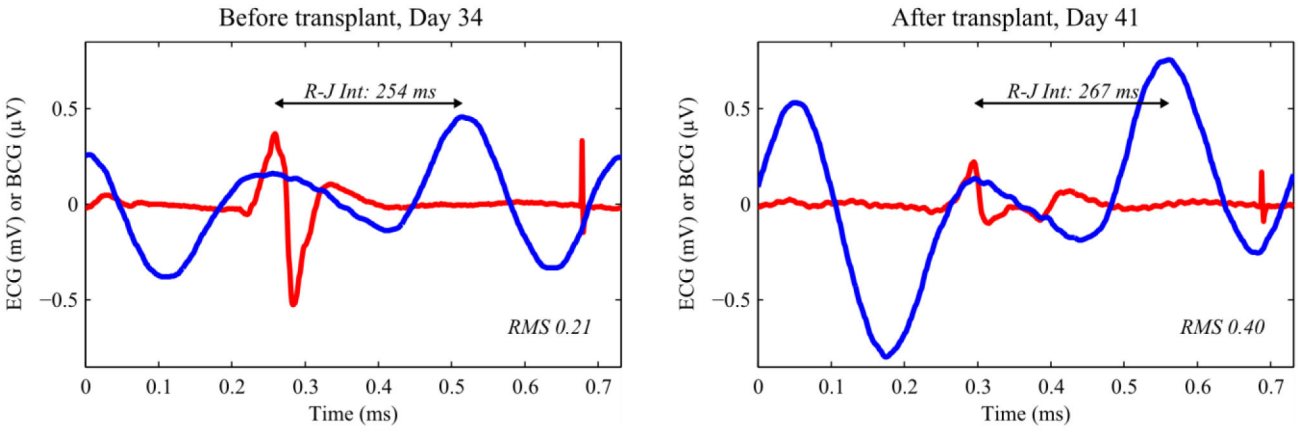


**Figure 3.**

BCG ensemble average for (left) pre and (right) post heart transplant. J interval is observed, reflecting the decreased inotrope dosage upon transplant. The post-transplant signal exhibits higher signal amplitude. An increased R-Pacemaker artifact is noted at the right of each figure.