Litterature Review On Ballistocardiograms Processing Tools

S. Otis

École de technologie Supérieure

samuel.otis.1@ens.etsmtl.ca

June 12, 2017

I. Introduction

Investigating vital signs in a non-obtrusive way has been of great interest in the last decade. Many cardiac and respiratory diseases would then be easier to track and gather results from. This would greatly help in classifying different patients with special health features. Many technologies are used to detect these signals, be they classical or new ways of acquiring them.

An interesting sensor newly developed is the fiber optic sensor (FOS). FOSs are a new way of acquiring the mechanical activity of the human body through the modulation of the light in response to an external perturbation during the transmission. They have been thoroughly used due to their high sensitivity and lower cost of production. More precisely, the microbend theory is used for building special types of FOS. Microbending of the optical fiber causes an attenuation of the light transmited through it, as per critical angle property [26]. Multiple pairs of microbenders, when displaced due to physical perturbation, squeezes the fiber. This causes more intensity loss in the cladding region of the optical fiber and increases in function of the pressure exerted on the sensor. Other known sensors are also used. Some mats with inbedded strain gauge or hydraulic sensor were developed and were mostly used to monitor respiratory and cardiac activity as well as body movements. Piezoelectric sensors with PVDF or EMFi material designed in a mat also monitored such signals.

The hardest signal to retrieve is certainly the cardiac activity. The Ballistocardiogram (BCG) measures the ballistic forces generated by the heart, that is, the mechanical response of the body when the heart ejects the blood into the vascular tree. This technique has been used since the late 19th century [7], but failed to justify its usefulness. Still, it has awakened much interest for bridging a gap in basic Electrocardiogram (ECG), that is, a new information about the actual state of the vascular tree and the pumping effect of the heart [24]. Lately, with the improvements of signal processing tools and technological advancements, the interest for the BCG was renewed. It is a most useful tool to obtain important information on the cardiac cycles as well as on the respiratory dynamics, while being unobtrusive. Analogously to the ECG, which possesses the so-called QRS complex describing the high-amplitude shape of the electrical stimulations during systolic and dystolic cycles, the BCG possesses the IJK complex. It is then possible to extract information such as the J-J intervals to characterize the cardiac rythm. One of the difficulties in analyzing such signals lie in getting rid of the motion artifacts, that is, when a person moves its body while trying to record the BCG. A large range of processing tools exist to analyze the raw signal coming from the sensors and extract the BCG as well as the breathing rate and body movements. The first tool coming to mind are the wavelet transform (WT). The WT is often used for signal denoising as well as for feature extraction. Its strength relies in its ability to split the signal into multiple frequency components. That is, we gain a spectro-temporal representation of this signal. The transform operation actually convolves the signal through a lowpass and a highpass filter, thus giving detail and smooth coefficients, representative of coarse and finer scale phenomenons. It is possible to go deeper in the decomposition levels by reapplying the passage into the filters to gain detail coefficients at finer scales. Compared to the Fourier transform, the wavelet transform is able to detect discontinuities in the signal without generating too much coefficients to characterize it. Another useful tool is the empirical mode decomposition (EMD). It is a modified method derived from the Hilbert Transform called the Hilbert-Huang transform [8]. This method decomposes a given signal in finite and smaller 'intrinsic mode functions'(IMFs). It then allows to see instantaneous frequencies as a function of time. Last but not least, the cepstrum is a long known processing technique often used for speech processing [17], based in the domain of the quefrencies. Still, its usefulness in terms of heart rate and breathing rate extraction is undeniable. The cepstrum is the inverse Fourier transform of the logarithmic spectrum of a signal. With this representation, we can uncover the fundamental periods of a signal, that is, the time occurence of certain signal such as heart and breathing rate.

II. Litterature Review

i. Sensors

Lots of efforts are directed toward the use of FOS for ballistocardiograms and other biomedical signals. Lau and al. [12] developed a microbend fiber optic sensor able to measure the force exerted on a sensor mat. This extremely sensitive mat was used in an MRI environment from the perspective of real-time measuring and recording of the breathing rate. The raw data went in a bandpass filter stage and a peak detection algorithm to retrieve the breathing rate of the patient. The novel sensor showed successfull results in acquiring an MRI in a respiratory-gated acquisition, thus preventing respiratory physiological noise from patients in the MRI.Chen and al. [3] also used a microbend FOS to extract the BCG from healthy subjects by applying band pass analog and digital filtering to the recorded signal. The BCG is measured on the back of a patient sitting on a chair. They used a NI acquisiton card and a running version of Labview on a computer to acquire the signal and filter it. Analogic filtering was successfully applied directly on the prototype to further reduce the cost of their system. Sadek and al. [23] used a Fiber Bragg Grating Sensor (FBG) to sample the BCG from ten subjects from under a thin bed sheet. Dziuda and al. [6] used an FBG to extract the breathing rate as well as the heart rate from a healthy subject. The sensor is placed between the back of the subject and the back of a chair and undergoes filtering, averaging and referencing with an ECG. Other than FOS sensor, researchers used other sensor type as described earlier. Pino and al. [20] retrieved the heart rythm using an EMFi piezoelectric sensor.

ii. Signal processing

An important step in retrieving the heart rate is, naturally, the use of a rigorous signal processing to extract the heart beats from the signal. Many sources of noise may pollute the signal, be it the "flicker" noise (1/f noise or pink noise) coming from the electrical equipment, the surrounding power line interference at 50 Hz or 60 Hz, depending on the geography, or the motion artifact noise. The biggest sources of noise are the motion and breathing artifacts, interfering with the measurements when the subject does even the smallest motion. To find the BCG in all these sources of noise, many signal processing tools from simple to complex ones are used.

Wavelet transform

Aiming to record vital signs in a non-obtrusive way, Postolache and al. [21] transformed the signal with a daubechie 4 wavelet base on eight levels of decomposition. They filtered the target coefficients with a moving average. Their study, based with 10 young subjects, was validated against a reference ECG and a spirometer for the breathing signal. The limit of their study, tough, lies with the use of strictly-sane subjects. Combining Donoho and Johnstone [5] wavelet shrinking method with a symlet 8 wavelet base, Jin and al. [9] detected the heart rate with a peak searching algorithm. Validation of their method is only visual using the graphs of their BCG and of the ECG. The study, done with one subject of unknown health state, doesn't give any expression of the heart rate according to time nor deals with the problem of motion artifacts. Many other teams also used wavelets with different mother wavelets basis to extract the BCG from the raw recordings. Delière and al. [4] implemented continuous wavelet tranform (CWT) with a morlet wavelet base to quantify the ballistocardiogram amplitude modulation induced by respiration (BAMR) in an imposed controlled breathing (ICB) protocol. The BAMR was expressed through the maximum local energy in each cardiac cycle. They could then investigate the heart rate variation (HRV) with the BCG reading rather than with the respiratory sinus arrhythmia(RSA) phenomenon, derived from the ECG. The results came from four healthy adults and showed good correlations correlation coefficient of 0.8466 between RSA and their new BAMR method. The validation was done between two estimated values, the RSA being calculated with their own algorithm from the RR interval (RRI) of the ECG. Sadek and al. [22] implemented the Maximal Overlap Direct Wavelet Transform (MODWT) to extract the BCG signal from a microbend FOS. This method proved far more faster than their precedent method using the CEEMDAN algorithm on the data taken on an FBG sensor mat with little more error on the measurements.They did so with a 8-vanishing moment Symlet wavelet base. They validated their study on 50 subjects with a reference ECG.

Pino and al. [20] compared the EMD and wavelet approach to detect the BCG. They used simple EMD decomposition to extract the BCG. The function modes 2 and 3 contained the heart rate signal but the wavelet approach showed nonetheless better results. Their wavelet approach used a Daubechie 6 wavelet base to extract the detail coefficients which contained the bcg signal. To validate their research, they used 54 voluntary subjects and a reference ECG. Their study was, though, sensible to motion artifacts, having some heart beats cover results as low as 48%. That is, 52% of the heart beats were not detected.

Empirical Mode Decomposition

Pinheiro and al. [19] also decomposed the BCG time series into few components and found the BCG in motionless recordings and were able to recover part of the heartbeat information. It still was unable to recover most of the information when a motion artifact is involved. They validated on eight subjects, one having a coronary stent, without any ECG reference. Their goal was more oriented toward online computing, achieving an excellent computing time of less than 1 ms per segment. Still, their study was limited by the size of the sample and the lack of ECG validation Following the ensemble EMD (EEMD) procedure, Song and al. [25] extracted the BCG for cardiovascular classification. They used temporal, frequential and non-linear methods to retrieve the heart rate in the BCG and then classify the features with a naive bayes classifier. They had no ECG reference since their study's goal was to classify diseases. Their best classification result was around 92%, combining all three heart rate methods. They still had difficulties managing motion artifacts.

Sadek and al. [23] used an enhanced version of the EEMD to extract the BCG from an FBG sensor. This method proved to be reliable. At the ninth decomposition component of the

CEEMDAN, they retrieved the heart rate with little error and, together with sensor fusion, they achieved a faster heart rate reading than with EEMD. Moreover, it was more efficient in dealing with motion artifacts and having sensor fusion. This study, done on 10 subjects, had an ECG reference to validate the results. The backfire of their method is the slow computing time of about 30 seconds for the CEEMDAN algorithm. The subjects were also all healthy, thus having ideal vital signs.

Machine Learning

Machine learning, with its recent popularity, has also been applied to extract vital signs from an unobtrusive sensor. Bruser and al. [1] extracted the heart rate with a clustering algorithm.The training phase generated the best prototype heart beat using clustering and kept the prototype amongst all the clusters which represented best the heart beat. They then used cross correlation between the rest of the signal and the prototype to find all the heart beats. Euclidian distance was also a mean to find the heart beats as well as the heart valve signal (HVS). They performed the validation on 16 healthy subjects, aiming their research to ideally detect cardiac arrhythmia. An lead-I ECG reference was used and they reported a heart beat coverage of nearly 96% with only 1.79% error. Nonetheless, the study is limited by the need to perform the training phase manually each time. They also have only one case of arrhythmia, which is not enough to pronounce results in this direction. Paalasmaa and Ranta [18] used also a clustering algorithm but with an ideal signal which they generated. Their detection rate of less than 50% was well below the one of Bruser and al. [2011]. The study was still validated with and ECG reference and 3 subjects. They yet have to find a better way of isolating the right cluster for representing the heart beat. As of now, they select the cluster with the biggest density. Following them are Noh and al. [16], who developed a portable module for heart rate detection. They preprocessed the raw signal coming from the sensor mat with a daubechie 4 wavelet base and applied a layer of template mathcing on top of it to increase robustness. The template is generated from the correlations in the input signal. They use the wavelets to filter and run a peak detection algorithm. The heart beats are also found by doing correlation again between the template and the rest of the input signals. The wavelets alone showed an efficiency of 94% in detecting the heartbeats of a sample of 10 students. With the ML layer, they increased the detection rate to 98%. The study is referenced with a lead-I ECG, but the authors do not give enough details as to how the template is generated. Moreover, all signals are ideal since all the subjects are healthy. More simple ML methods were used and proved efficient. With a simple logistical binomial regression, Katz and al. [10] classidied interbeat intervals (IBI). Done on 14 healthy subjects and validated with and ECG lead-II, they had a maximum error of 20.75 ms on the duration of the IBI between two beats. They aim to base future works on arrhythmia, though this topic is very lightly taken on.

Cepstrum

The cepstrum, as described before, has been applied with good results to estimate the heart rate. Bruser and al. [2] made the mean of the spectrum recorded on different sensors with a sliding window and then converted it to the cepstrum domain. With a simple peak detection, it was possible to find back the heart rate. Their BedS method had a deviation of 150 ms in the IBIs. On 28 subjects suspected of different sleep disorder, they gathered the precedent results, validating with a reference ECG. Though they used subjects with sleep disorder, they do not pronounce themselves on any of the disorders based on the recordings. Zhu and al. [27] used the same approach by extractng the cepstrum from a sliding window algorithm. They then filtered the cepstrum to make easier finding the heart rate peak. Achieving an error around 1% for the whole recordings, they validated the system with a reference ECG on 10 healthy subjects. The study did not show any way of dealing with motion artifacts. In another study, Zhu and al. [28] detected the breathing rate using a similar approach but with many multiresolution windows on three mats containing 6 sensors each. Their results all had a very small error below 1%. Validated with a respiratory inducted plethysmography (RIP) belt on 10 healhy subjects, they still had no approach concerning motion artifacts. The system also had a big number of sensors which needs to be scaled down. Kortelainen and al. [11] extracted the heart and breathing rate using many windows containing two beats per window. Then, by applying the cepstrum on these windows and looking at the difference between two consecutive cepstrums, they achieved 0.4% error on the heart rate and 1.5% error on the breathing rate. The study, aimed at sleep apnea, was validated on 28 subjects suspected of apnea with a RIP belt and ECG reference. Motion artifacts was not dealt with in this study.

Other methods

Lots of others methods were developed using simpler processing tools. Lee and al. [13] applied heart and breathing rate detection on two babies with a simple band pass filter and moving average window. They detected 95% of the beats in average with an error of 1.53%. Peak detection retrieved the heart beats, with an ECG reference and respiratory sensor. This study has a really small amount of subjects for validation though, and was not tested against motion artifacts. Mack and al .[15] used an infinite impulse response (IIR) bidirectionnal filter and detected local peaks in the signal. With a special peak searching algorithm, they isolated all probable peaks and derived the heart and breathing rate on 40 subjects with ECG and RIP belt. They were interested about sleep apnea too, but had no automatic detection of apnea phases during sleep monitoring. Lastly, Lydon and al. [14] used a band pass filter and a short moving average window to extract the energy from 0.3 s segments. They computed the heart rate with these windows and adjusted the last computed heart rate with a moving average of the estimate. Their method had a maximum of 1.85% error. One group of three young subjects and another of four elderly subjects helped validate their study. The reference was a piezoelectric finger sensor. Motion artifacts and posture were not included in the results.

III. Conclusion

Many teams around the world use common sensors and new ones to extract heart and breathing rate in a non-obtrussive way. Lots of processing tools were tested and validated for doing so and presented good results on retrieving vital features in characterising the cardiac and respiratory activity. The wavelet tranform seem to offer good tradeof between precision and performance. Moreover, ML can add an extra layer of robustness on any algorithm. The litterature showed no comparative study of different processing tools or methods to negate motion artifacts pollution of the signal, this would be a good opening for more research on the topics.

Publication	Sensor Type	Target signal	Processing Tool
[12]	MFOS	BR	BPF
[3]	MFOS	HR	BPF
[23]	FBG	HR	EMD
[6]	FBG	BR/HR	BPF
[20]	EMFi	HR	WT/EMD
[21]	EMFi	BR/HR	WT
[9]	-	HR	WT
[4]	-	HR	WT
[22]	MFOS	HR	WT
[19]	EMFi	HR	EMD
[25]	FS	HR	EMD
[1]	FS	HR	ML
[18]	Piezo FS	HR	ML
[16]	LCS	HR	WT/ML
[10]	PFS	HR	ML
[2]	PVDF	HR	CS
[27]	FBG	HR	CS
[28]	FBG	BR	CS
[11]	PS	HR	CS
[13]	LCS	BR/HR	BPF
[15]	FCP	BR/HR	BPF
[14]	PS	HR	BPF

Table 1: *Summary of other researches in the litterature. MFOS : Microbend Fiber Optic Sensor; FBG : Fiber Bragg-Grating; FS : Force Sensor; PFS : Piezoelectric Force Sensor; PS : Pressure Sensor; LCS : Load Cell Sensor; FCP : Force Coupling Pad; HR : Heart Rate; BR : Breathing Rate; BPF : Band Pass Filter; WT : Wavelet Transform; EMD : Empirical Mode Decomposition; ML : Machine Learning; CS : Cepstrum*

References

[1] C. Bruser, K. Stadlthanner, S. de Waele, and S. Leonhardt. Adaptive Beat-to-Beat Heart Rate Estimation in Ballistocardiograms. *IEEE Transactions on Information Technology in Biomedicine*, 15(5):778–786, September 2011.

[2] C. Brüser, J. M. Kortelainen, S. Winter, M. Tenhunen, J. Pärkkä, and S. Leonhardt. Improvement of Force-Sensor-Based Heart Rate Estimation Using Multichannel Data Fusion. *IEEE Journal of Biomedical and Health Informatics*, 19(1):227–235, January 2015.

[3] Zhihao Chen, Ju Teng Teo, Soon Huat Ng, and Xiufeng Yang. Portable fiber optic ballistocardiogram sensor for home use. page 82180X, February 2012.

[4] Q. Delière, J. Tank, I. Funtova, E. Luchitskaya, D. Gall, P. Van de Borne, and P. F. Migeotte. Ballistocardiogram amplitude modulation induced by respiration: a wavelet approach. In *2015 Computing in Cardiology Conference (CinC)*, pages 313–316, September 2015.

[5] David L. Donoho and Iain M. Johnstone. Adapting to Unknown Smoothness via Wavelet Shrinkage. *Journal of the American Statistical Association*, 90(432):1200, December 1995.

[6] L. Dziuda, F. W. Skibniewski, M. Krej, and J. Lewandowski. Monitoring Respiration and Cardiac Activity Using Fiber Bragg Grating-Based Sensor. *IEEE Transactions on Biomedical Engineering*, 59(7):1934–1942, July 2012.

[7] J. W. Gordon. Certain molar movements of the human body produced by the circulation of the blood. *Journal of Anatomy and Physiology*, 11(Pt 3):533, 1877.

[8] Norden E. Huang, Zheng Shen, Steven R. Long, Manli C. Wu, Hsing H. Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung, and Henry H. Liu. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 454(1971):903–995, March 1998.

[9] J. Jin, X. Wang, S. Li, and Y. Wu. A Novel Heart Rate Detection Algorithm in Ballistocardiogram Based on Wavelet Transform. In *2009 Second International Workshop on Knowledge Discovery and Data Mining*, pages 76–79, January 2009.

[10] Y. Katz, R. Karasik, and Z. Shinar. Contact-free piezo electric sensor used for real-time analysis of inter beat interval series. In *2016 Computing in Cardiology Conference (CinC)*, pages 769–772, September 2016.

[11] J. M. Kortelainen, M. van Gils, and J. Pärkkä. Multichannel bed pressure sensor for sleep monitoring. In *2012 Computing in Cardiology*, pages 313–316, September 2012.

[12] D. Lau, Z. Chen, J. T. Teo, S. H. Ng, H. Rumpel, Y. Lian, H. Yang, and P. L. Kei. Intensity-Modulated Microbend Fiber Optic Sensor for Respiratory Monitoring and Gating During MRI. *IEEE Transactions on Biomedical Engineering*, 60(9):2655–2662, September 2013.

[13] W. K. Lee, H. Yoon, D. W. Jung, S. H. Hwang, and K. S. Park. Ballistocardiogram of baby during sleep. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 7167–7170, August 2015.

[14] K. Lydon, B. Y. Su, L. Rosales, M. Enayati, K. C. Ho, M. Rantz, and M. Skubic. Robust heartbeat detection from in-home ballistocardiogram signals of older adults using a bed sensor. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 7175–7179, August 2015.

[15] D. C. Mack, J. T. Patrie, P. M. Suratt, R. A. Felder, and M. Alwan. Development and Preliminary Validation of Heart Rate and Breathing Rate Detection Using a Passive, Ballistocardiography-Based Sleep Monitoring System. *IEEE Transactions on Information Technology in Biomedicine*, 13(1):111–120, January 2009.

[16] Yun-Hong Noh, Soo-Young Ye, and Do-Un Jeong. Development of the BCG feature extraction methods for unconstrained heart monitoring. In *5th International Conference on Computer Sciences and Convergence Information Technology*, pages 923–928, November 2010.

[17] Alan V. Oppenheim and Ronald W. Schafer. From frequency to quefrency: A history of the cepstrum. *IEEE signal processing Magazine*, 21(5):95–106, 2004.

[18] Joonas Paalasmaa and Mika Ranta. Detecting heartbeats in the ballistocardiogram with clustering. In *Proceedings of the ICML/UAI/COLT 2008 Workshop on Machine Learning for Health-Care Applications, Helsinki, Finland*, volume 9, 2008.

[19] E. C. Pinheiro, O. A. Postolache, and P. S. Girão. Online heart rate estimation in unstable ballistocardiographic records. In *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, pages 939–942, August 2010.

[20] E. J. Pino, J. A. P. Chávez, and P. Aqueveque. Noninvasive ambulatory measurement system of cardiac activity. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 7622–7625, August 2015.

[21] O. Postolache, P. S. Girao, G. Postolache, and M. Pereira. Vital Signs Monitoring System Based on EMFi Sensors and Wavelet Analysis. In *2007 IEEE Instrumentation Measurement Technology Conference IMTC 2007*, pages 1–4, May 2007.

[22] I. Sadek, J. Biswas, B. Abdulrazak, Z. Haihong, and M. Mokhtari. Continuous and unconstrained vital signs monitoring with ballistocardiogram sensors in headrest position. In *2017 IEEE EMBS International Conference on Biomedical Health Informatics (BHI)*, pages 289–292, 2017.

[23] I. Sadek, J. Biswas, V. F. S. Fook, and M. Mokhtari. Automatic heart rate detection from FBG sensors using sensor fusion and enhanced empirical mode decomposition. In *2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, pages 349–353, December 2015.

[24] M. L. Singewald. Ballistocardiography: past, present, future. *Annals of Internal Medicine*, 41(6):1124–1133, December 1954.

[25] Y. Song, H. Ni, X. Zhou, W. Zhao, and T. Wang. Extracting Features for Cardiovascular Disease Classification Based on Ballistocardiography. In *2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom)*, pages 1230–1235, August 2015.

[26] Eric Udd. An overview of fiber-optic sensors. *review of scientific instruments*, 66(8):4015–4030, 1995.

[27] Y. Zhu, V. F. S. Fook, E. H. Jianzhong, J. Maniyeri, C. Guan, H. Zhang, E. P. Jiliang, and J. Biswas. Heart rate estimation from FBG sensors using cepstrum analysis and sensor fusion. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 5365–5368, August 2014.

[28] Y. Zhu, J. Maniyeri, V. F. S. Fook, and H. Zhang. Estimating respiratory rate from FBG optical sensors by using signal quality measurement. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 853–856, August 2015.