Measurement, processing and analysis of stress magnetocardiograms

C Kesavaraja, S Sengottuvel, Rajesh Patel, Pathan Fayaz Khan, Pragyna Parimita Swain and K Gireesan

SQUIDs and Applications Section, Condensed Matter Physics Division, Indira Gandhi Centre for Atomic Research, Homi Bhabha National Institute, Kalpakkam-603 102, India

E-mail: kesavaraja@igcar.gov.in

Abstract: Magnetocardiography (MCG) measures weak magnetic fields originating due to the electrical activity of the heart. MCG offers distinct diagnostic information on the cardiac electrophysiology in a variety of dysfunctions. This list includes myocardial ischemia, which is associated with reduced blood supply to the heart, electrically manifested as changes in the ST segment of the cardiac cycle. As opposed to the conventional measurement of electrocardiogram (ECG) on subjects undergoing physical stress test to investigate these ST changes, rest MCG itself has been demonstrated to be more sensitive. Considerable interest exists among researchers to investigate MCG signals measured during physical exertion as well to explore the possibilities of improvements in its sensitivity. This paper portrays the MCG measurements of a few subjects under rest and during moderate cycling in supine posture using a non-magnetic bicycle ergometer. The work details the signal processing steps followed in processing MCG to refine the signal quality in computing the parameter, ST fluctuation score in an automated manner. Significant changes are seen on the ST fluctuation scores measured on a few healthy subjects across rest and stress conditions. These results persuade its possible use on MCG measured on subjects with ischemic heart diseases by treating this analysis as baseline measurements.

Keywords: Magnetocardiography, stress MCG, automatic detection, ST fluctuation score, Ischemic heart diseases

1. INTRODUCTION

Magnetocardiography (MCG) measures the magnetic fields generated by the electrical activity of the heart. While the electrocardiogram (ECG) records voltage distribution (on some standard locations on the thorax and limbs of subjects) arising due to cardiac electrophysiology, the physical quantities that are measured in these two modalities are different. Hence ECG and MCG complement each other in offering the diagnostic information on the health status of the heart [1]. The magnetic fields generated by the heart are extremely weak of the order of 50-100 pico Tesla which are several orders of magnitude weaker than the earth’s magnetic field and other electromagnetic interferences present in the ambience. Secondly, extremely sensitive magnetic field detectors such as the superconducting quantum interference devices (SQUIDs) operating at a working temperature of 4.2 K are required to measure these weak cardiac magnetic fields. To facilitate the fullest detection limit of SQUID sensors, these measurements are usually performed inside magnetically shielded environments to record MCG with a very high signal-to-noise ratio [2]. MCG measurements are leadless and non-invasive and are
performed by positioning the subjects supinely with thorax closer to the lower end of liquid Helium containers inside which the SQUID sensors are bathed. MCG is appreciated for its sensitivity in detecting and stratifying the risks associated with certain life-threatening cardiac dysfunctions including ischemic heart diseases (or in other words coronary artery diseases). Partial or complete blockages of coronary arteries which carry blood to the heart cause ischemia to the muscles of the heart that are serviced by the affected arteries and might lead to myocardial infarction or death of those muscles if untreated. Myocardial infarction is one of the major causes of death in developing countries and is alarmingly increasing among the members of young age groups also. Hence early detection of ischemic heart diseases and detailed cardiac assessments using potential non-invasive measurement modalities are always preferred to propose a mass screening for heart health check-up. While the electrical signatures pertaining to the reduced blood supply to the heart manifest as subtle changes in the ST segment of the cardiac cycle, measurements performed during treadmill exercise tests are known to exemplify these changes to be recorded and quantified in ECG. On the other hand, MCG measured under rest condition itself has been shown to be sensitive to detect ischemic heart disease, but with limited success [3-6]. Hence, conducting stress MCG is preferred for detailed cardiac electrophysiological evaluations. However, unlike a treadmill ECG, stress MCG necessitates subjects to perform mild exercise in supine posture using non-magnetic arrangements, not to introduce any additional noise to the measurement system, which is likely to be detrimental to the already weak cardiac signals. More to this, biological noise which arise from subjects like for example breathing of subjects, body movements etc. are unavoidable and so the extraction of the useful signal components of interest are difficult and calls for signal processing algorithms to attenuate unwanted noise.

This work reports the measurement and analysis of exercise MCG made using a custom-made non-magnetic patient bed attached with a bicycle ergometer to perform recordings under rest, exercise and recovery conditions. Processing of MCG signals using techniques to cancel drifts, high frequency noise and automated identification of fiducial points on the cardiac cycle to isolate region of interest for quantifying the signal variations which are quintessential for the diagnosis of ischemic heart diseases have been outlined.

2. METHODS

MCG measurements were performed inside a two layered magnetically shielded room consisting of alternate layers of mu-metal and Aluminium. A flat bottomed four channel MCG [2] system populated with a square array of low transition temperature; direct current biased SQUID sensors coupled to superconducting first order axial gradiometers was used. The inter-sensor spacing was 4.2 cm and the warm to cold distance of the cryostat was about 1.0 cm. The measurement bandwidth set was 0-300 Hz. Typical noise floor of the system operating at a temperature of 4.2 K was 12 femto Tesla/√ (Hz). MCG measurements were carried on seven healthy male subjects (29 + 7 years) in a supine posture with the position of the sensors (inside the cryostat) closer to the anterior chest over the mid-sternal line. A fibre reinforced plastic bed consisting of X-Y lead screws was used to position the lying down subjects comfortably under the cryostat. The bed consisted of a pedalling arrangement at the level of the foot of subjects which could be adjusted depending on the height of subjects. The pedalling assembly consisted of plastic pedals attached to a pulley whose contact with a brake shoe could be adjusted in such a way to increase the resistance to the pedalling action for exerting a commensurate increase in physical stress to subjects while cycling. The arrangement for performing stress MCG is shown in Figure 1. Each measurement session consisted of MCG recorded with subjects not performing pedalling action, mild to moderate pedalling, followed by rest condition.
Fig. 1. A four channel SQUID MCG cryostat mounted on a non-magnetic gantry is shown. The X-Y movable patient table with pedaling assembly are also shown. A subject doing a mild pedaling exercise with his chest held closer to the tail of the cryostat for MCG measurement inside the shielded room.

These experimental sessions were designated as rest, exercise and recovery phases respectively each spanning for five minutes duration. The analog signals from all four SQUID channels were simultaneously digitized by a data acquisition system with a resolution of 24 bits at a sampling rate of 1 kHz. Informed consent was obtained from all the subjects participated in the study and they did not have any discomfort during and after the experimental sessions.

2.1 Signal Processing
The raw as recorded MCG contained drifts and other noise whose elimination was crucial for quantifying the changes in the ST segment. A sequence of signal processing procedures followed for this purpose is depicted in Figure 2 as a flowchart. The raw MCG data was processed using wavelet transform technique to eliminate DC offset and baseline drift [3]. The wavelet coefficients, which contained baseline wander, drifts and other movement related artifacts were identified and eliminated from the raw data. The baseline drift and other high frequency noise were mildly higher in magnitude for the exercise case as compared to those in rest. The baseline drift corrected MCG time series was epoched with respect to the time instants of the R wave peak in every beat. The time instants of the R peak were identified using Pan and Tompkins algorithm. The detailed description of algorithm could be found elsewhere [7]. The epoched beats were averaged by selecting nominally identical cardiac cycles by correlation measure. The signal-to-noise ratio of the averaged traces in each measurement location significantly improved depending on the number of cardiac cycles taken for averaging, which varied between at least 150-250 beats in each case depending on the variations on the heart rate of subjects. The outputs of each stages of processing are shown in Figure 3. The raw as recorded MCG shows significant baseline drift due to breathing of subjects. The red colour traces shown in the figure are the isolated baseline drifts in both the rest and exercise case which is subtracted from their respective raw data to get drift corrected MCG as shown in the figure. It could be seen that high frequency signals occur as wiggles which are reduced by averaging them based on the R wave peak instants to generate a single representative beat with an improved signal-to-noise ratio in both rest as well as exercise MCG.
An automated algorithm [3] was used to identify the QRS-offset time instant of signal averaged MCG time series for each subject in all the three measurement conditions. The averaged MCG cardiac cycle is differentiated to eliminate slowly varying signals such as the P and T wave and highlight only those pertaining to the QRS complex. The differentiated signal was then represented with their absolute values to exhibit as a trace with only positive deflections. The absolute value curve was smoothed with a six point moving window average filter and then fitted to a standard first order Gaussian model. Fitted Gaussian curve is normalized based on its maximum value. Tangent passing through the falling slope of the Gaussian curve is drawn and the point of intersection of this straight line with the x-axis is taken to be the QRS-offset time instant [8]. Similarly, the T wave onset was obtained automatically by finding the slope in the rising portion of the T wave [9]. A window was created to isolate the time segment between the algorithmically identified QRS offset and the onset of the T wave, the region of interest viz., the ST segment. The ST segment was normalized to quantify the fluctuations occurring between the QRS offset and the T wave. This procedure is illustrated in Figure 4 and 5.

**Fig 2.** Flow chart describing post processing of MCG signal time series for quantifying the ST changes.
Fig 3. (a), (b) and (c) represent the raw, baseline corrected and averaged MCG signals of a subject in rest condition. (d), (e) and (f) represent the raw, baseline corrected and averaged MCG of the same subject during moderate exercise.

Fig 4. A signal averaged MCG trace (blue trace) and the signal converted as a fitted Gaussian shape (red trace) with tangent (black line) passing through the point of trailing slope on the Gaussian curve, the point of intersection of the tangent with the X-axis, the QRS offset (red pointer).
Fig 5. (a) A signal averaged MCG trace (blue trace) with tangent (black line) passing through the point of positive slope on the T wave and its intersection with the horizontal dotted line determining the onset of T wave
(b) Normalized ST segment.

The ST fluctuation score is computed by using the equations (1) and (2)

\[ y(j) = \frac{B_{r}(t_{i})}{\text{max}(B_{r})} \]  

(1)

\[ S = \{|y(1)| + |y(M)| + \sum_{j=2}^{M} |y(j) - y(j-1)|\}.M \]  

(2)

where ‘y’ - averaged, filtered and normalized signal, ‘M’ is the total no of extrema and ‘j’ is the index of extrema.

The procedure followed in the analysis of high frequency fluctuations occurring within the QRS complex with time duration less than 120 ms, termed as the intra-QRS fragmentations was adapted for finding the ST segment fluctuation score [10-12]. The fluctuations in the ST segment were quantified by calculating the sum of the absolute values of the differences in neighbouring extrema (spans). In addition, the absolute values of the first and the last remaining extrema were added to this sum. The ST fluctuation score was calculated as the multiplication of the determined sum by the number of extrema. This single quantity reflects the fluctuation covering the number of peaks and their heights within the ST-segment of the signal-averaged magnetocardiogram. All these processing steps were performed on all the subjects in the three measurement conditions to compute the ST fluctuation scores. The differences in the subsequent time instants of the R wave peak were determined from each case to compute heart rate variability. The mean heart rate was tabulated along with the ST fluctuation score for all the cases.

3. RESULTS AND DISCUSSIONS

| Subject | Heart rate | ST Score | % Change (Stress-Rest)/Rest x100 |
|---------|------------|----------|----------------------------------|
|         | Rest (BPM) | Stress (BPM) | Recovery (BPM) | Rest | Stress | Recovery |
| 1       | 80         | 88        | 87               | 58.41 | 49.81 | 60.96   | -14.72  |
| 2       | 83         | 92        | 84               | 77.59 | 70.21 | 74.98   | -9.5    |
| 3       | 92         | 101       | 94               | 54.66 | 31.12 | 52.26   | -43.06  |
| 4       | 88         | 98        | 78               | 51.79 | 25.19 | 62.42   | -43     |
| 5       | 87         | 99        | 79               | 51.50 | 25.13 | 56.44   | -51.2   |
| 6       | 65         | 83        | 67               | 68.07 | 20.79 | 46.27   | -69.4   |
| 7       | 67         | 86        | 84               | 83.13 | 38.43 | 74.70   | -53.77  |
In this paper the effect of exercise on the cardiac signals during the repolarisation period was investigated. The ST fluctuation score in different physical conditions (rest, stress and recovery) was computed and the statistical significance of the score values was analysed. Table 1 shows the ST fluctuation scores and mean HR in beat per minute (BPM) and the percentage change in the fluctuation values during stress. As could be seen, during exercise (stress), the ST fluctuation score decreases and was statistically significant (p<0.0042). There was no difference in fluctuation scores in rest and recovery (p=0.56) as expected. The mean HR was an indicator to qualify the level of change in the cardiac dynamics due to stress in each case. It could be observed that though the signal averaged representative beat in both the conditions look alike with hardly noticeable difference visibly, the fluctuation score calculated between the two reveals subtle differences between the two. Decrease in the ST score for ischemic heart disease during stress was reported earlier by researchers [13], the results obtained in this study might help as a baseline condition to evaluate anomalous variations in ischemic conditions. The sensitivity offered by SQUIDs to detect signals with frequencies close to d.c is a conducive aspect employed to probe the absolute changes in ST [1] and the present study attempts to utilise this aspect.

However, it is to be noted that these quantifications take a helping hand from signal treatments and automation routines to accomplish this task. It is possible that since these changes are weak, they are vulnerable to be corrupted even by baseline drifts in addition to high frequency wiggles. This analysis is also expected to facilitate interpretation of cardiac magnetic fields using multi-channel MCG measurements covering the whole anterior thorax. Extensive analysis is required to investigate further on the severity of the fluctuation scores with respect to change in heart rates to be performed on a large group of people with different age and gender.

ACKNOWLEDGMENT

The authors thank Mr. Baskaran, Dr. N.V. Chandra Shekar, Dr. Shaju K Albert for encouragement and support. Dr. Raja J Selvaraj and Dr. Santhosh Satheesh, Cardiologists at JIPMER, Puducherry are acknowledged for their suggestions and refinements in the signal processing methodology.

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