# NEW ROBUST METHODS FOR DETECTION OF SYSTOLIC COMPLEXES IN THE SIGNAL ACQUIRED FROM QUANTITATIVE SEISMOCARDIOGRAPH

M. Jirina, P. Smrcka, Z. Trefny, K. Hana

Czech Technical University in Prague, Faculty for Biomedical Engineering,
Zikova 4, 166 36, Prague 6, Czech Republic

jirina@ubmi.cvut.cz, smrcka@ubmi.cvut.cz, trefny@ubmi.cvut.cz, hana@ubmi.cvut.cz

**Abstract: Quantitative seismocardiography is a simple and non-invasive method of measuring compression waves generated by heart activity. It provides important information about the cardiovascular system. The first important information acquired from quantitative seismocardiogram (QSCG) is the pseudo-period rate. This paper focuses just on the detection of pseudo-periods in the QSCG signal. Two methods of detection together with a method of sophisticated data preprocessing are presented. The results of the methods are demonstrated using real data.**

## Introduction

The QSCG device detects cardiac vibrations as they affect the entire body; the measuring sensors (solid-state accelerometers) are usually placed in the plate of the chair – additional instruments applied on the proband's body are not required. The results of the QSCG analysis are usable in various clinical fields ([1], [3]). The first and most important step in the process of detection of significant characteristics of measured QSCG curves is to detect pseudo-periods in the signal regardless of the initial pseudo-period position. Other characteristics can be acquired by a relatively simple process over the appointed pseudo-period. This contribution deals with the preprocessing and automatic computer-based detection of beat pseudo-periods in middle-time QSCG records. Two independent approaches have been used to appoint the pseudo-periods – the first method is more precise and is intended for off-line QSCG analysis, the second method is easy, robust and is appropriate for real-time QSCG processing.

## Data Acquisition and Preprocessing

For the development and evaluation of the proposed methods, we used 46 digital records of the QSCG, each 5 min length. The probands were placed in the sitting position and during the monitoring only very light physical activity (such as PC keyboard typing) was allowed. The experimental data were acquired using a solid state accelerometer built into the chair plate. The actual sampling frequency was 500Hz, and the resolution of the A/D converter was 16 bits.

Raw data acquired from a QSCG suffer from a wide range of imperfections. The most significant drawback of the device is its high sensitivity to unintentional movements of the patient. To gain important characteristics from the signal that would correctly describe the state of the patient, it is necessary to keep stable measurement conditions and especially to keep the patient in a motionless position for a long period. Typically, one reliable measurement takes about five minutes. It is obvious that for such a long period it is impossible for the patient to keep motionless. Unexpected motion which is unintentionally incorporated into the signal as an error is manifested by abrupt changes in the signal.

Performing a correct measurement depends on a physician or another expert who should get the best data from the device for further processing. Such data has been acquired in cooperation with physicians. Hence, we were able to focus only on data processing.

Due to the character and known origin of the data, we should pre-process them to obtain a unified form for further reliable processing. A typical error that damages the signal is the impulse noise. This is due to the device itself. Fortunately, this kind of error is easily removable by simple median filtering. In our case we used the median filter followed by a sliding averaging filter. In this way we have removed both the impulse noise due to the measuring system and slightly smoothed the signal for better work with it.

Further, we calculated the trend of the signal by smoothing the signal over a long sliding window and consequently we subtracted the trend from the signal. In this way we removed part of the influence of the respiratory system. We emphasize that just breathing has a non-negligible influence on the signal shape because it is manifested by pressure (or actually by force) that adds to the actual signal we are looking for.


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Finally, we normalized the whole signal to zero mean and unit deviation. Such normalization is useful and justified because the zero mean is common also for abrupt changes due to the patient's movement (position conservation – if the patient raised himself up he must later slump). The unit deviation is less justified but can be used because abrupt changes are fortunately far less frequent and thus does not significantly influence the deviation. Moreover, from the viewpoint of the solved task such normalization is fully adequate.

*Detection of Wrong Parts of Signal:* A signal from seismocardiograph suffers from many fake signals. It is due to the fact that the signal is measured as a force (acceleration) and therefore each movement of the patient has a significant influence on the signal course. As the signal of interest is weak, it has to be gained. Therefore other disturbing signals are gained too that can lead to significant steep changes of the signal. If the patient moves his/her body the changes are easily detectable but the movement can be due to the breathing and other less important movements within the body. Such changes influence the signal but are worse detectable.

One possible solution of the problem is to train a neural network on correct courses of the signal to predict the signal and consequently to try the neural network to predict the actual signal. As the actual signal can suffer from the above artifacts and the neural network does not incorporate these artifacts, the predicted will be with high probability wrong too and thus significantly different from the course. This situation is thus welcomed because provides information about differences between the predicted and actual signal. Is such situation occurs we can simply identify the wrong interval and exclude it from the signal for further processing.

We used a multilayer perceptron neural network with one hidden layer and one output layer. The hidden layer has 30 nodes with sigmoid activation function and the output layer has single node with linear activation function. The standard backpropagation training algorithm has been used. We used three sets of data. One for training, one for validation and one for testing. The sets have been compiled from original data in the ratio 2:1:1. The whole data set has been compiled from single series of time values of the signal as consecutively shifted values within a window size of 50 samples. The length of prediction is one sample at a time. More values is possible but the larger length of prediction the worse results. The length of prediction to 10 future values is still fully acceptable.

## Methods

Two original methods of detection are presented. The first method was developed for precise off-line detection of QSCG pseudo-periods. Automatic removal of misclassified pseudo-periods is incorporated into the method. The second method was developed for real-time detection of QSCG pseudo-periods and important reference points inside the systolic complex.

*Method A for precise off-line detection, Enhancement of Pseudo-periods:* The main and most significant task is to detect (appoint) beginnings and/or endings of the pseudo-periods. By having such distinct marks on the signal we can then easily deduct characteristics describing important features of the patient's cardiovascular system for further evaluation by physicians.

Looking at the signal, a person can relatively easily mark the beginnings and/or endings of the pseudo-periods, see the top part of Figure 2. We can see that during one pseudo-period a large swing followed by lower ones occurs. The smaller swings are unimportant at this moment but worsen automatic detection of the significant swing. In the theory of signal processing, the square of the signal is often used to emphasize large peaks. In our case this is not possible because in this way we would generate fake peaks near the significant swing. This would be due to the large negative swing preceding the main positive swing and only the length of the raising edge for the main swing is utilized in the further described swing detection method. Hence, we use the cubic exponent in the power of the signal to conserve the pseudo-symmetrical character of the signal in accordance with the main swing emphasis. In this way we significantly scale the signal and therefore we re-normalize the signal back to zero mean (which remained almost zero) and unit deviation, see the top part of Figure 1.

This method seems to be auspicious but applying this transformation to the whole signal course can cause some parts of the signal to become unbalanced. Therefore we suggest applying of the cubic power only on a short section (window) of the signal and after that to shift the window by one sample and repeat the transformation in the new shifted window. In this way we obtain many transformed signals that we cumulate and finally compute their average, see bottom parts of Figure 1 and Figure 2. Such a transformed signal is more balanced than by simple applying the cubic power on the whole signal. The sliding widow size should be as close to the actual average pseudo-period as possible. A shorter window enhances undesirable noise within pseudo-periods. On the contrary, a larger window depreciates the advantage of this method and it leads to the same results as when using the cubic power transformation applied to the whole signal. A re-normalization of the transformed signal to zero mean and unit deviation is naturally also used.


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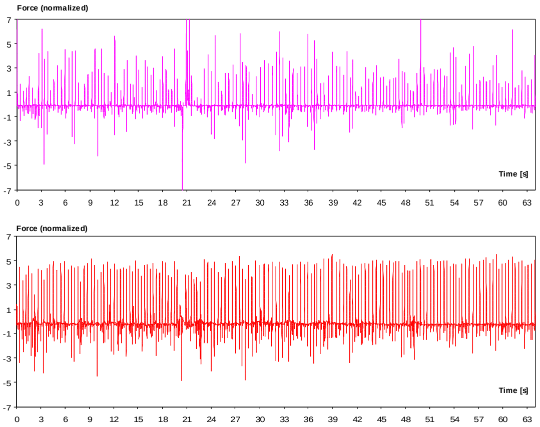


Figure 1: Top: Simple Cubic Power of the Signal, Bottom: Composed Shifted Cubic Power of the Signal.

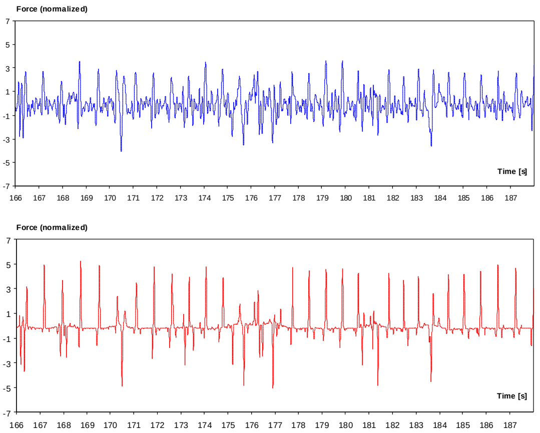


Figure 2: Top: Part of the Original Signal, Bottom: Composed Shifted Cubic Power of a Part of the Original Signal.

*Method A for precise off-line detection, Pseudo-period Detection:* The actual method of detection of pseudo-periods is based on detection of significant swings (enhanced by the method introduced above) and runs this way, see Figure 3. The signal is passed from left to right and the lengths of monotonic rises of the signal are computed. In this way we obtain plenty of lengths. We proceed from the fact that the largest monotonic rises signal just the most important swings within the pseudo-periods and thus can be used to delimitate them. The significant lengths should thus correspond to important and visually recognizable swings of the signal in each pseudo-period.

There is the question of how to appoint the threshold over which the lengths should correspond to the pseudo-period swing. We proceed from the assumption that the pseudo-periods should have approximately a similar length (due to the sophisticated transformation described above). Therefore, we move the threshold from the minimum to maximum value of the monotonic rises and measure the deviation of the pseudo-period lengths normalized by their mean. For some thresholds there should be minimal deviation and therefore the corresponding time point should limit the pseudo-periods, see Figure 4.

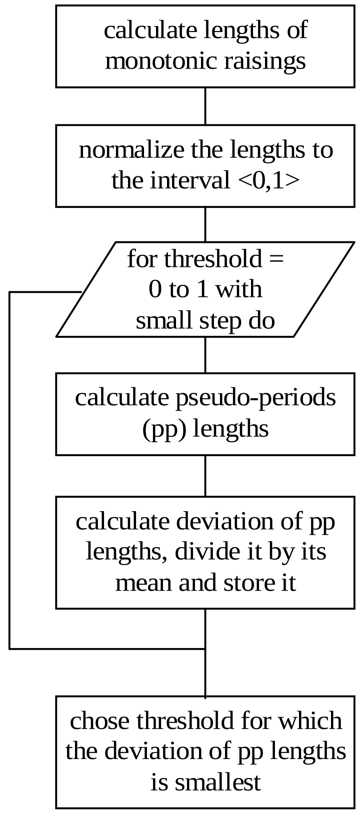


Figure 3: Diagram of pseudo-period detection.

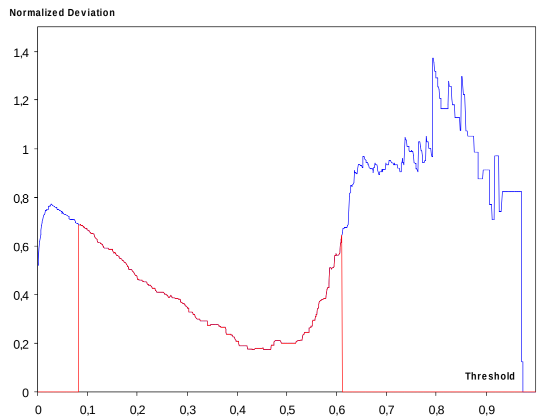


Figure 4: Deviation of pseudo-periods vs. threshold.

At the moment we have the signal still with some excesses. These are due to incorrectly detected over-abundant or on the contrary overlooked pseudo-periods, see Figure 5.


ISSN: 1727-1983 

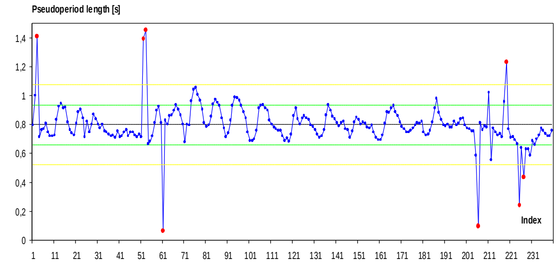


Figure 5: Pseudo-period length vs. pseudo-period index.

The simplest way how to manage these excesses is to omit the whole interval but this will lead to the loss of part of the information. Another way is to attempt to recover the pseudo-period(s). Over-abundant pseudo-periods are manifested by down peaks with two points on each peak on the graph of pseudo-period lengths. This is due to the fact that the split pseudo-period behaves like two smaller pseudo-periods. We can recognize this situation by simple threshold of the lengths and eliminate it by adding the corresponding lengths together. For the threshold a double value of deviation has been used. Similarly, overlooked pseudo-periods can be also detected by threshold, this time in the top part of the course in the graph of pseudo-period lengths. The same threshold value as in the previous case has been used. Elimination of overlooked pseudo-periods consists in splitting them into so many parts to prove similar lengths as neighboring pseudo-periods.

The final processed signal after eliminating over-abundant and overlooked pseudo-periods is depicted in Figure 6.

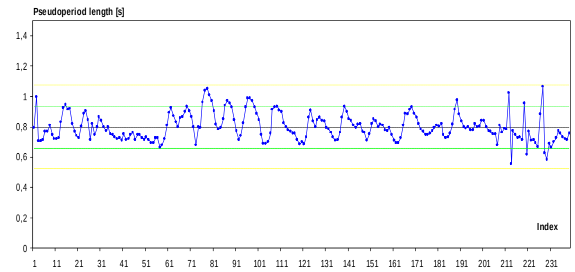


Figure 6: Pseudo-period length vs. pseudo-period index.

*Method B for robust real-time detection:* While the off-line method A is more sophisticated, method B is relatively simple and was developed for the detection of QSCG pseudo-periods in real time.

The method is derived from a well-known and robust algorithm for QRS complex detection in traditional electrocardiograms (ECG), originally developed by Hamilton et al. The algorithm was based on the first derivative of the input signal and many thresholds and parameters are automatically adapted to individual changes in the input signal using sophisticated empirical rules. The results (position of the dominant – so-called R - wave) are obtained with some detection delay (above 200 ms). For details on the algorithm, see [2].

For our purposes it is important that the initial values of many parameters are adjustable and by modification of these values the original method was slightly adapted to QSCG's different curve morphology. Namely the following parameters were changed: (1) length of the first derivative from the original 10 ms to 80 ms, (2) length of the high-pass pre-filter from 125 ms to 350 ms, (3) length of moving window integration from 80 ms to 200 ms. Optimal values were selected experimentally in order to achieve the best detection results.

Additionally, we developed a special backward searching process for the precise detection of the position of the I-wave and J-wave in each QSCG pseudo-period.

The function of the whole algorithm is as follows: output of the traditional ECG QRS detector gives the rough position of the systolic complex inside the QSCG - candidate X. Then the specific morphology of the QSCG curve is utilized to backward search the position of the J-wave – we expect the first big negative peak in MTI samples (about 100 ms). If the detection is successful, we assign the position of the peak as the I-wave; see Figure 7.

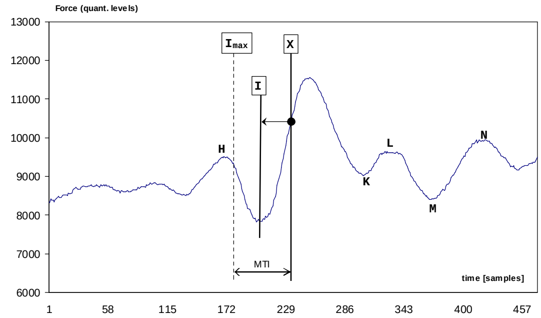


Figure 7: Backward local I-peak searching in the QSCG cycle.

Finally we search forward for the position of the J-wave, which we expect to be the first big positive peak in maximally MTJ samples (about 160 ms), see Figure 8.

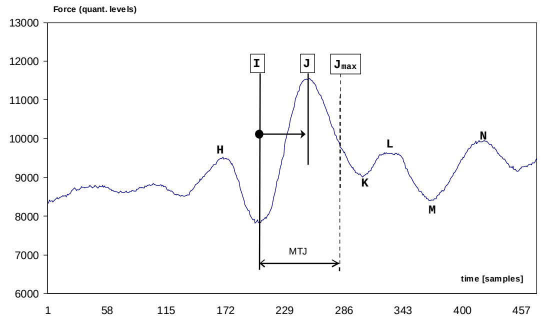


Figure 8: Forward local J-peak searching in the QSCG cycle.


ISSN: 1727-1983 

For the peak-detection we used a very simple method based on the first difference (length 15 ms): when the transition from negative to positive value of the difference occurs, then the sequence is marked as a negative peak; the transition from a positive to negative difference means a positive peak. If searching for the J-wave or the I-wave fails, candidate “X” is rejected and the algorithm continues without detection of the QSCG pseudo-period.

The rejection of “candidate X” is very important step and it increases robustness of the whole detection procedure against the artifacts – see demonstration on the Figure 9.

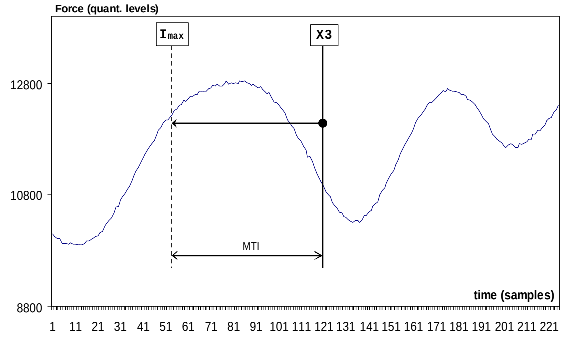


Figure 9: Rejection of the false beat detection. We search backward from “candidate X3” for the first big negative peak. The I-wave must be recognized in MTI samples (about 100 ms), so in this case the detection was not successful.

The false detection of the dominant “candidate X”, which is not a true QSCG cycle, was corrected by the proposed simple backward searching algorithm, because the morphology in the nearest neighborhood of the point X3 does not match the detection rules – backward searching for the I-wave in MTI samples was not successful, the false positive detection of the systolic complex was correctly rejected.

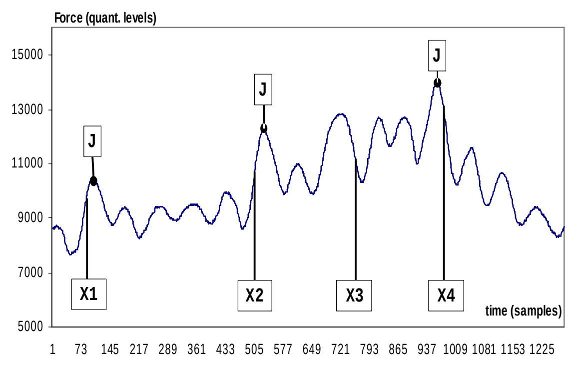


Figure 10: Result of the whole detection: false candidate X3 was correctly rejected.

**Results**

For the development and evaluation of the proposed methods, we used 46 digital records of the BCG, each 5 min length. We focused our attention on correct detection of I-wave and J-wave positions in these records. We performed a simple comparison of both methods with the results obtained from a human expert by visual observation of the digitized QSCG signal and manual placing markers in appropriate positions (I-wave, J-wave). For the results, see tab. I. The human expert placed markers in relevant positions in all cases; total number of detected (I, J)-pairs in all 46 records was 15641. Then we tested efficiency of the proposed 2 algorithms (A, B) in the same situation. We evaluated the results of the automatic detection relatively in comparison with the results obtained from a human expert (assumed as 100% success). For example, the algorithm “A” correctly detected 15172 I-waves of total 15641; it means 97%.

Table 1: Evaluation of Proposed 2 Algorithms (A, B)

| | **I-wave** | **J-wave** |
|---|---|---|
| Human expert | 100 % | 100 % |
| Algorithm A | 97 % | 95 % |
| Algorithm B | 94 % | 93 % |

**Discussion**

For high-quality measurements we can obtain good-looking signals for which both methods exhibit excellent results. For disruptive and spurious signals there is still a good chance of obtaining authentic information because we first detect the impairments and remove the particular interval of the signal. It is true that in using this method we also remove certain useful information but simultaneously ensure processing of the remaining signal. We emphasize that we need not process all consecutive pseudo-periods in the signal but only a sufficient amount of pseudo-periods.

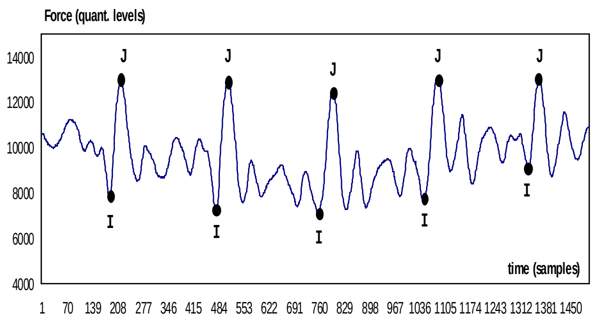


Figure 11: Typical QSCG signal with correctly placed reference points.


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For good-looking and typical signals, the methods behave very well, achieving nearly complete success (see Figure 11). The success decreases with deterioration of the signal. On the other way, in such signals it is often difficult even for the human expert to recognize correct pseudo-period time points (see Figure 12).

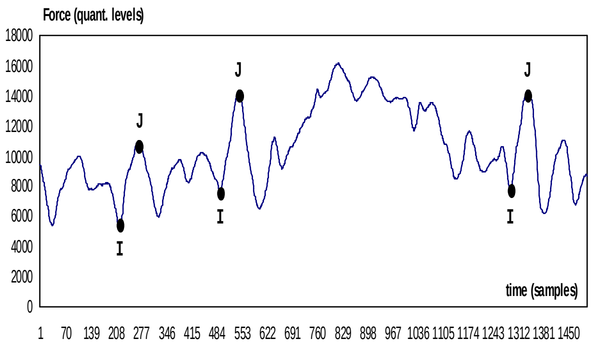


Figure 12: QSCG signal with the motion artifact; it is difficult to recognize correct positions of some reference points.

## Conclusions

Two suggested methods were applied to the preprocessed signal. The first one is based on the observation that the longest monotonic raising should signalize the pseudo-period origin. Automatic removing of misclassified (overlooked and over-abundant) pseudo-periods is incorporated into the method. The second method is based on modified well-known Hamilton-Tompkins algorithm for QRS detection in traditional ECG, adapted to BCG's different curve morphology; this method is prepared for operation in real-time.

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