

ADAPTIVE RR PREDICTION FOR CARDIAC MRI

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ABSTRACT

Cardiac magnetic resonance imaging (MRI) is very challenging due to the perpetual heart movements. This movement is pseudo-periodic and implies several issues for image acquisition. Building a single image requires several shots, done on a specific timing of the cardiac cycle. Nowadays the heart rate is estimated before imaging and then it is assumed not to evolve during acquisition. Additionally, in order to remove motion artifacts, the patients are asked to perform breath-holds. Unfortunately, while performing a breath-hold, the heart rate is changing in a significant way. To address this problem in the framework of clinical applications, we propose a simple method to predict the out-coming RR interval, in order to compute adapted MR parameters. The RR interval is the time separating two consecutive R waves and corresponds to one cardiac cycle. Due to its simplicity this method is clinically applicable. The prediction is performed by modeling the heart rate variation as a linear combination of different sensors (here, respiratory sensor and amplitude of R wave). We evaluated this method on five healthy subjects in a clinical setup.

Index Terms— Heart rate, MRI, Electrocardiography, prediction method.

1. INTRODUCTION

1.1. MR Cardiac Timing

Cardiac MRI sequences are generally synchronized on the R wave of the Electrocardiogram (ECG) (see fig. 1) and the read out is done during the ventricular diastole. Depending on the heart rate (HR) and so on the RR interval, optimal trigger delay (TD), acquisition time (AT) and trigger window (TW) are defined before scanning. Additionally for black blood imaging, Inversion recovery (IR) pulses are usually played directly on the R wave to have an inversion time (TI) of the blood on read out [1], [2]. These MR parameters are set before the scanning and are computed when the patient is breathing normally. In order to avoid motion artifacts, cardiac imaging is done while patients are performing a breath-hold. HR is assumed to be constant during breath-hold. So for black blood imaging, the trigger launch the IR pulse and the image acquisition follows with a delay fixed to acquire during diastole. The aim of this study was first to show that this assumption is generally violated and that the currently used procedure can reduce image quality. Furthermore black blood imaging for patients with a $HR > 85$ beat-per-minute (*bpm*) is theoretically unfeasible, because TI

of blood is then greater than the RR interval. In the same way, accurate acquisition during systolic phase is not possible, because IR pulses should be played before the R wave. This study will then introduce a new method for computing MR parameters based on the variation of HR [3] and which would enable the acquisition of black blood systolic images for every patient. For this aim predicting the HR variation during apnea is required. We will see that RR prediction is even possible during free breathing and will be useful for double gating systems, i.e. gating of the heart activity and respiratory position. The proposed method will be easily implemented in actual MR systems or triggering devices. They can be used clinically without further constraints for the patient and the medical staff and without lengthening of the examination duration.

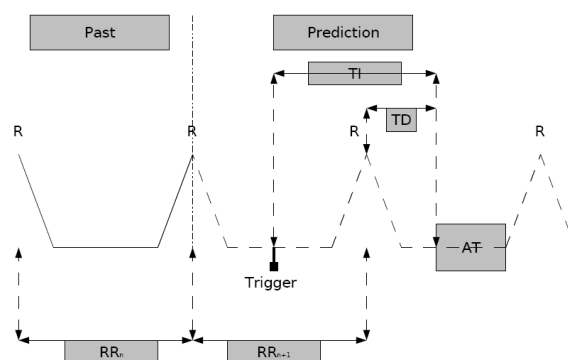


Fig. 1. Schematic of an ECG trace and Acquisition Timing. In this example, the IR pulse is played in the heart cycle previous to the acquisition.

1.2. Preliminary Analysis

The first step of the study was to analyze the HR variation in two different breath-hold modes (inspiration and expiration) in five subjects. We observed that HR variation during apnea is not reproducible between the two modes (see fig. 2). Moreover the reproducibility between different subjects was not obvious. In opposite it appeared that the behavior of HR for a same subject, in the same breath-hold mode is quite similar.

Since several breath-holds are performed by one patient during an examination, the information of the HR variation during the first breath-hold could be used in order to compute

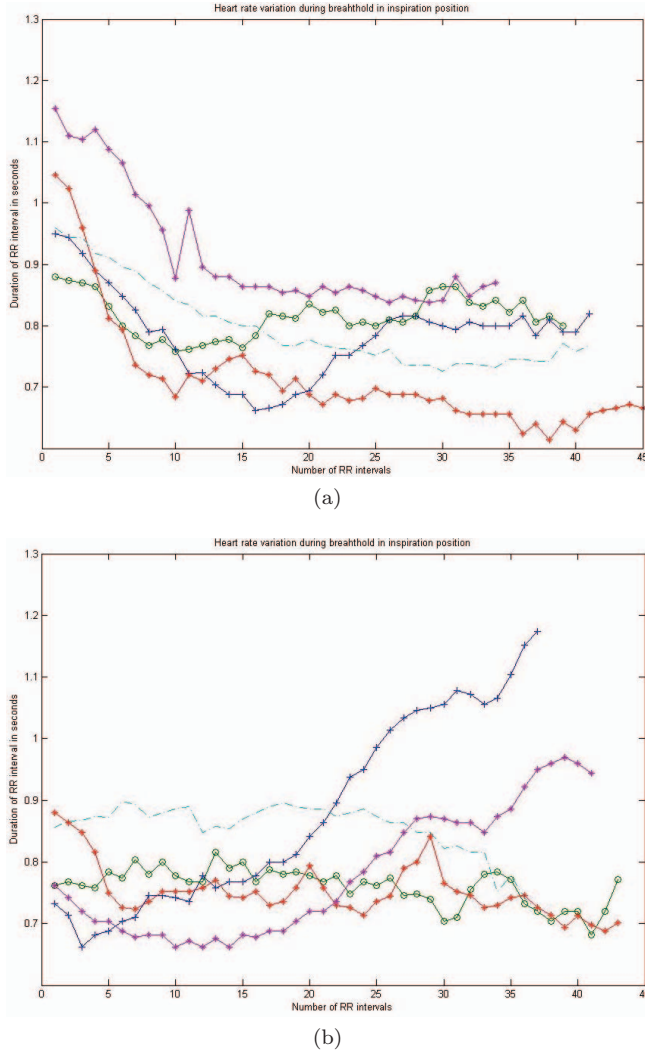


Fig. 2. Heart rate variation during breath-hold in inspiration 2(a) and in expiration 2(b). Each curve represents the HR for one subject. X axis represents the cardiac cycle number and Y axis represents the RR interval duration in seconds.

the parameters of a prediction model of the RR during the others. Currently, a patient has to perform several breath-holds during one MR examination that could all be used for modeling. The model for prediction must be quite simple and not require a long period of training since one breath-hold contains generally less than thirty cardiac cycles. This means that complex models such as neural networks cannot be used for clinical purposes. Thus we first tried a simple AR model with a low order, so that the training can be done during one apnea and prediction can easily be implemented in real-time [4]. We have implemented this method in the SAEC [5] in order to achieve systolic cardiac MRI. We have used a Fast Spin Echo sequence and the trigger was sent to the MR system using the scheme presented in figure 1. The prediction was computed using only the past RR. The results are displayed in figure 3.

In this paper, we present a new model for prediction. To

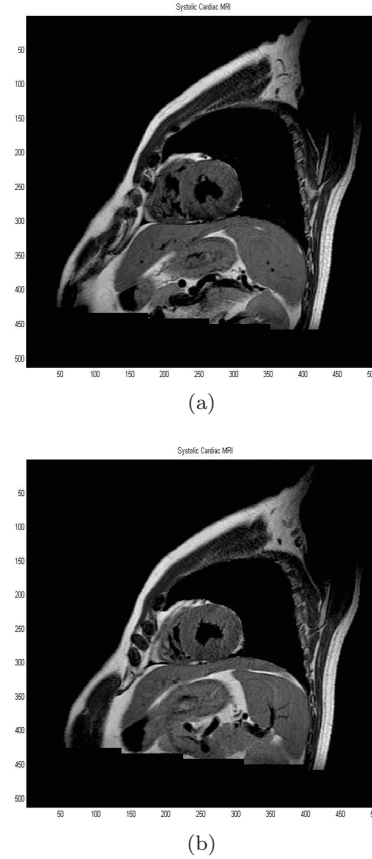


Fig. 3. Systolic Cardiac Images in little axis, using RR prediction, two different slices 3(a), 3(b). Such images are unfeasible with the clinical applications.

estimate the model parameters on-line a Kalman-filter-based method is used.

2. THEORY

We propose to apply a physiological multi input regression (PMIR) using information of multiple physiological sensors. In our case, we used cardiac and respiratory physiological changes. For respiration information we combined two methods, (i) a pneumatic belt on the subject's abdomen and (ii) the variation of the the R waves magnitude. These new inputs will bring information since it is known that HR is correlated with respiration, and called the respiratory sinus arrhythmia (RSA). The HR decreases during inspiration and increases in the other case. Using this information can improve the prediction especially for free breathing sequences. The signal of the belt is non-uniformly sampled, so we used only the samples when HR is computed. As described in [6], the magnitude of QRS is correlated with respiration, this information should be very useful during breath-holds, since it is always available.

The assumption done is that the RR interval is a linear combination of the previous RR, the respiration, its derivation and the magnitude of the previous RR.

Let X_n be the HR, R_n the signal of the respiratory belt at

QRS time n , R'_n the derivation the respiratory belt at QRS time n and A_n the amplitude of the n^{th} QRS, then the PMIR can be written as :

$$X_n = \sum_{i=1}^{p_1} a_i X_{n-i} + \sum_{i=1}^{p_2} b_i R_{n-i} + \sum_{i=1}^{p_3} c_i R'_{n-i} + \sum_{i=1}^{p_4} d_i A_{n-i} + \varepsilon_n. \quad (1)$$

The parameters will be estimated using a Kalman filter since this modeling corresponds to a state vector model. In fact, equation 1 can be seen as the observation equation of a Kalman filter system.

$$y_n = H_n \underline{x}_n + \varepsilon_n, \quad (2)$$

where $y_n = X_n$ is the observation vector,

$H_n = [X_1, \dots, X_{p_1}, R_1, \dots, R_{p_2}, R'_1, \dots, R'_{p_3}, A_1, \dots, A_{p_4}]$ is the observation model and the parameters

$\underline{x}_n = [a_1 \dots a_{p_1} b_1 \dots b_{p_2} c_1 \dots c_{p_3} d_1 \dots d_{p_4}]^T$ is supposed to be the state vector.

As we have no information about their evolution during the examination, we suppose that it is almost constant. So the state equation can be written as :

$$\underline{x}_{n+1} = \underline{x}_n + \underline{u}_n. \quad (3)$$

We assume the dynamic noise and measurement noise (resp. \underline{u}_n and ε_n) are both Gaussian distributed with zero mean and constant covariance.

So we are in front of a state estimation problem given the observations up to n ($y_{1..n}$).

The first breath-hold is used to initialize the model parameters.

3. METHODS

Five healthy subjects performed two breath-holds in inspiration and two others in expiration. The subjects were in supine position inside the MR bore of a 1.5T General Electrics SIGNA Excite HD MR system (General Electrics, Milwaukee, WI). Each breath-hold lasted at least for 30 seconds. Signal from a respiratory belt and ECG were carried by a Maglife (Schiller Médical, Wissembourg, France) patient monitoring system and recorded along with MRI gradients and acquisition window signal on the Signal Analyzer and Event Controller (SAEC) custom computer and electronics [5]. All the data were collected for offline processing (but were implemented in the SAEC so as to achieve real-time imaging). In order to evaluate HR variation we used R waves detection algorithm used in an industrial monitoring device (Argus PB-1000, Schiller AG, Baar, Switzerland). This detection is quite a difficult task when the ECG is collected in a MR environment. Many works have shown that the artifacts induced by MR gradients can produce false triggering. Some methods for ECG denoising and MR gradient artifacts suppression have been developed. In order to improve automatic detection of R waves, we preprocessed the ECG signal by using a singular value decomposition based method [5]. Since some R-waves were still missed, the annotations had been corrected manually.

Three kinds of PMIR have been tested, the difference consists in the number of used parameters, this is explained in table 1. Each different PMIR has a number, and the p_i parameter is the order of the regression for each signal, as defined in

equation (1).

The prediction using PMIR with different state observation

Table 1. Difference of the three PMIR

	PMIR 1	PMIR 2	PMIR 3
p_1	2	2	2
p_2	2	2	0
p_3	2	2	0
p_4	2	0	0

was analyzed. The criteria chosen is the MSE which is defined as in equation 4.

$$MSE = 1/n \times \sum_{i=1}^n (\hat{x}_i - x_i)^2. \quad (4)$$

4. RESULTS

This study shows that the assumption that heart rate is constant during breath-holding is unwarranted. Computing MR parameters, in order to fit at best the RR interval will then improve the quality of MR images, in particular for Black blood images as discussed in introduction.

We can see on figure 4 that the shape of predicted HR variation with PMIR is globally the same as the real HR variation. In fact, as few samples are available, we are obliged to make the system very sensitive to changes in order to adapt very fast.

For better comprehension, the MSEs have been normalized by the MSE obtained with a constant RR.

The improvement of the MSE compared to a constant RR estimate is quite evident regarding the results approximately six to seven times better (tables 2, 3).

Table 2. Normalized MSE results of prediction using PMIR for HR variation during breath-hold in inspiration position

Subject Id	PMIR 1	PMIR 2	PMIR 3	RR =
S1	0.11	0.09	0.08	1
S2	0.55	0.45	0.45	1
S3	0.09	0.08	0.07	1
S4	0.06	0.05	0.04	1
S5	0.35	0.29	0.25	1

Table 3. Normalized MSE results of prediction using a PMIR for HR variation during breath-hold in expiration position

Subject Id	PMIR 1	PMIR 2	PMIR 3	RR =
S1	0.2	0.15	0.24	1
S2	1.22	0.88	0.91	1
S3	0.53	0.44	0.45	1
S4	0.39	0.29	0.3	1
S5	0.03	0.02	0.02	1

5. DISCUSSION

Our method is based on physiological signals evolution as inputs of the models. It is obvious that during a breath-hold

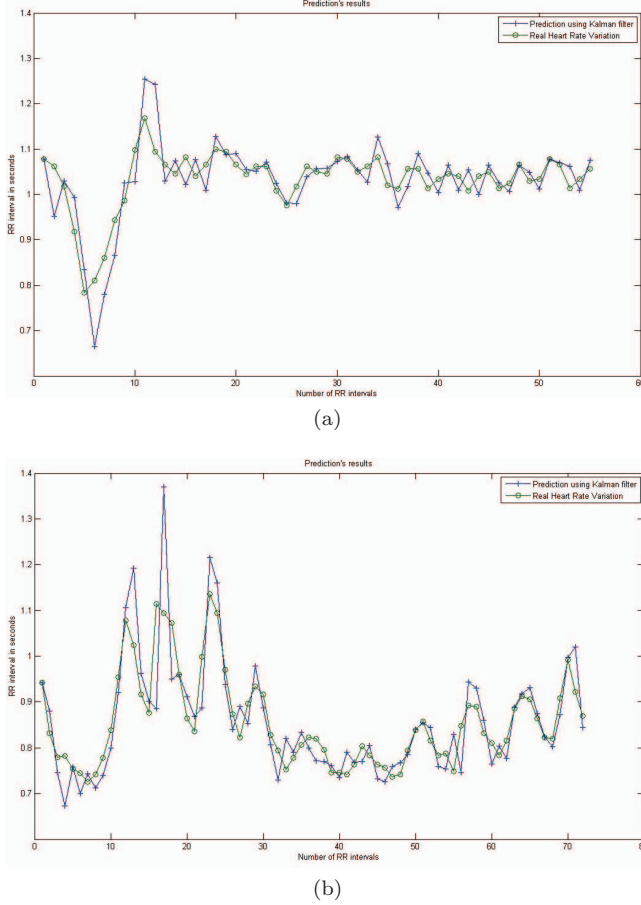


Fig. 4. Results of the method using PMIR 2 during free breathing 4(a) and large breathing 4(b). \circ represent the real HR variation and $+$ represent the prediction values using PMIR 2.

these variations are small and correspond to a low input in the model. However the breath-hold is never achieved perfectly due mainly to a drift in the position and this probably affects heart rate variation. Application in free breathing or double gating will benefit more from such a method.

Comparing the three PMIR proposed, we observe that using PMIR 3 gives the best results for breath-holds in inspiration position. This can be explained by the fact that there is probably some compensatory abdominal motions to hold the breath.

In the opposite, the PMIR 2 is better for breath-holds in expiration position. This can be explained by the fact that the abdomen is much more stable, since it is much more difficult to hold breath in expiration position, the respiratory belt contains more useful information.

Using the prediction will lead to the elimination of wrong cardiac time acquisitions that produce the ghosting artifacts. Unfortunately this will not remove motion artifacts, due to the movement of the subject. Thus it is difficult to compare two images done on two consecutive breath-holds with each strategy, since the quality of the subject's breath-hold cannot be controlled. This may have a great impact on image qual-

ity, with apparition of motion artifacts if the breath is not perfectly held.

Moreover, finding a relevant criteria for assessing the image quality in relation to the presence of ghosting artifacts onto the image is not a trivial task.

6. CONCLUSION AND PERSPECTIVES

Our method based on very basic assumptions, can be very efficient. Taking into account the HR variation during the acquisition can remove artifacts due to incorrect acquisitions. Due to its simplicity, this method is clinically applicable on actual MR systems and without lengthening the examination duration.

Complicating the model will certainly increase the quality of prediction, but so will the amount of data needed and the computation time such that the new method would not be clinically applicable anymore. Using more breath-holds in order to enhance the parameters estimation may provide better results. One of the drawback of this method is that sampling the respiratory sensor at the R-wave leads to a great loss of information. Using asynchronous methods could certainly improve the prediction.

7. REFERENCES

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8. ACKNOWLEDGMENT

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