

# Collection of Pediatric ECG Data for Testing Detection Algorithms in Automated External Defibrillators

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## Abstract

*Arrhythmia detection algorithms in Automated External Defibrillators (AEDs) need a special approval for use in children aged 0–8 years. Our aim is to establish a pediatric ECG reference dataset with rhythm annotations for the assessment of arrhythmia detection algorithms of AEDs.*

*The database will consist of a training dataset with a public interface for end-users to optimize their algorithms and an independent validation data set that remains hidden.*

*Currently we collected and analyzed 534 pediatric ECGs with non-shockable heart rhythms. We characterized the signal automatically by estimating noise level, power line interferences and movement artifacts. Also RR intervals and extrasystoles are automatically annotated.*

*In combination with additional clinical annotations the pediatric ECG dataset provides an instrument for the development and assessment of AED algorithms for arrhythmia detection in children.*

## 1. Introduction

AEDs are devices which are used to recover patients from sudden cardiac arrest. They are available in public places like train stations, shopping centres and government offices and can be used by laypersons. The portable electronic device automatically diagnoses life threatening cardiac arrhythmia and delivers an electrical shock in order to restore the normal heart rhythm.

The arrhythmia detection algorithms of the AED are developed on the basis of non-shockable and shockable ECG data. Shockable heart rhythms are ventricular fibrillation (VF) or ventricular tachycardia (VT).

In the past the use of AEDs was recommended only for adults, because their application to children would require modifications in the arrhythmia detection algorithm as well as in the shock delivery electronics. Furthermore, sudden cardiac arrests are ten times less common in children than in adults. However, the emotional and

social impact of cardiac failure in children is enormous [1]. So since 2005, the European Resuscitation Council (ERC) Guidelines recommend the use of AEDs for children aged 1–8 years [2]. In 2010 the ERC Guidelines indicate that the risk/benefit ratio may be favourable and the use of an AED should be considered even for children younger than 1 year [3].

Because children are anatomically and physiologically different from adults, the manufacturers of AEDs must verify their detection algorithms on pediatric ECGs. Some studies utilise proprietary pediatric ECG databases [4–6], but a public dataset for that purpose does not exist so far.

The aim of our work is to create a collection of pediatric ECG data from children younger than 9 years. The dataset should support the assessment of arrhythmia detection algorithms in AEDs. Also rhythm annotations and the signal quality of the data will be automatically characterized.

## 2. Methods

For the formation of the database special requirements are defined. All collected ECGs were divided into two age groups: younger than one year and between 1 and 8 years.

Table 1. Requirements of rhythm samples in the pediatric ECG database (NSR – normal sinus rhythm, AF – atrial fibrillation, SB – sinus bradycardia, SVT – supraventricular tachycardia).

Rhythms	required number
<i>Shockable</i>	> 80
- Coarse VF	
- Rapid VT	
<i>Non-shockable</i>	
- NSR	> 200
- AF, SB, SVT, Heart Block, Extrasystoles	> 60

For every age group a minimum of 80 shockable ECGs and a minimum of 260 non-shockable ECGs are required. The detailed specification for the number of rhythm samples is summarized in Table 1.

The ECG recordings of every age group are divided into a training dataset and a validation dataset. While the training dataset can be used for the development of new algorithms, the validation dataset remains hidden and thus provides the possibility to evaluate the performance of the new arrhythmia detection algorithms.

### 2.1. Collecting ECG samples

The non-shockable ECGs are collected in a pediatric cardiology centre in Berlin under informed consent of the parents. All data are anonymized. The 12 lead ECG data are recorded by using a digital ECG recorder (CardioLink® CL1000, Getemed, Teltow/Germany). The sampling rate is 500 Hz and only ECG recordings with a minimum length of 10 seconds are included in the database. The ECG data are converted in two open data formats: WFDB [7] und Unisens [8]. All ECGs are evaluated by a cardiologist.

### 2.2. Signal quality analysis

In order to determine the quality of the ECG recordings, we analyzed different simple and robust signal parameters of every non-shockable ECG so far. The main focus was on the lead Einthoven II which is very similar to the signal of the defibrillator pads.

The noise level is estimated by a moving window method. The smallest determined root mean square value in a moving window of 40 ms duration over the whole measurement is an estimation of the background noise level.

The signal amplitude is estimated by moving a window with a length of 150 ms consecutively over the signal. The averages of all peak to peak values of all windows in one recording were regarded as a rough estimator of the signal amplitude.

For detection of power line interferences (50 Hz) we moved a window with a length of 1 s in steps of 500 ms over the signal and generated a Fast Fourier Transformation of every window. The averaged amplitude of the 50 Hz line in all windows is used for assessment of power line interferences.

### 2.3. RR interval analysis

Before RR interval analysis the QRS complexes must be identified. As a preprocessor for the QRS detection we used a complex narrow band pass filter based on a modified Morlet wavelet. The resulting signal shows high amplitudes only during the QRS complexes. The local

maxima larger than a threshold were identified as QRS complexes [9].

Inspection of the RR intervals allows classifying extrasystoles, sinus arrhythmia rhythms and motion artifacts.

The automatically gained beat annotations form a part of the database.

## 3. Results

### 3.1. Characteristics of database

At the moment the ECG database includes 534 non-shockable recordings from 519 patients and 2 shockable ECGs.

Shockable pediatric ECGs are rare events because VF and VT incidence is lower in children than in adults. Currently we accelerate the effort to acquire more shockable rhythms for the database.

Table 2. Status quo of rhythm samples in the pediatric ECG database.

Rhythms	< 1 year	1-8 years
<i>Shockable</i>		
- Coarse VF	0	1
- Rapid VT	0	1
<i>Non-shockable</i>		
- NSR	137	272
- AF	0	0
- SB	0	0
- SVT	0	0
- Heart block	49	72
- Extrasystoles	0	4

Table 2 shows a summary of all previously collected ECGs. 121 recordings contain incomplete right bundle branch block patterns and 4 ECGs have extrasystoles. 348 non-shockable samples come from patients between 1 and 8 years and 186 non-shockable ECGs are from patients younger than one year. The minimum of 200 ECGs (Table 1) is attained in this age group with an average age of 3.89 years.

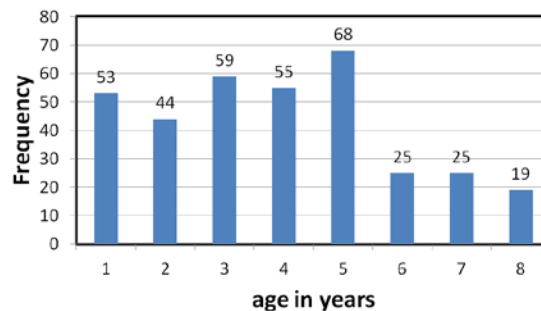


Figure 1. Histogram of the age distribution of the patients.

The histogram in Figure 1 shows the age distribution of the patients between 1 and 8 years.

Due to movement artifacts, it is not an easy task to record continuous ECG signals especially in younger children. In our ECG database we included only rhythm samples with a minimum duration of 10 seconds. The mean value of the ECG length of patients younger than one year was 25.03 s ( $\pm 12.89$  s) and the mean ECG length of the patients between 1 and 8 years was 27.08 s ( $\pm 12.36$  s). Figure 2 provides an overview of the distribution of the ECG length for both age groups.

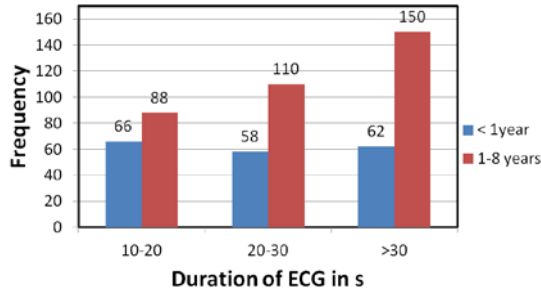


Figure 2. Histogram of the ECG length of the two age groups.

### 3.2. Signal quality analysis

The ECG signal samples exhibit variable noise levels. Noise sources are physiological noise caused by the patient such as muscle noise or breathing and electrical noise like power line interferences or amplifier saturation.

Figure 3 summarizes the results of the noise and power line interferences analysis. The mean noise amplitude for all ECGs in the database without filtering was  $15 \mu\text{V}$  ( $\pm 19 \mu\text{V}$ ). The mean signal amplitude was  $763 \mu\text{V}$  ( $\pm 242 \mu\text{V}$ ). Significant deviations of the mean values occur during motion artifacts. In 210 of the 534 ECGs in the database we had to cut out highly disturbed signal intervals.

The mean 50 Hz amplitude over all recordings was  $29 \mu\text{V}$  ( $\pm 26 \mu\text{V}$ ).

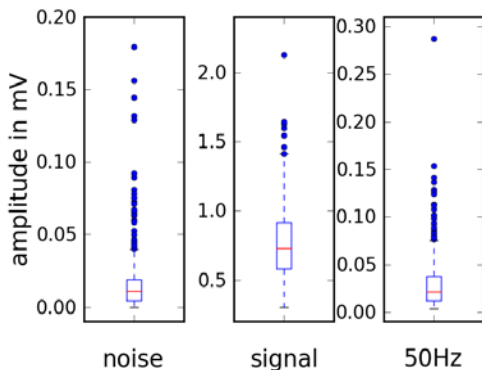


Figure 3. Box plots of noise, signal and 50 Hz amplitudes.

### 3.3. RR interval analysis

The RR interval length depends on the age of the subject. Normal heart rate is decreasing with age (Figure 4). The mean heart rate of all RR intervals was 117 bpm ( $\pm 30$  bpm).

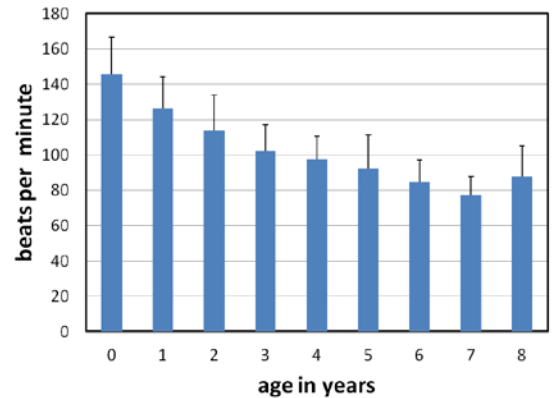


Figure 4. Dependence of all ECGs in the database on heart rate and age (mean value and standard deviation of all ECGs in the respective age group).

For every ECG we constructed a tachogram and labeled the mean RR value. Strong deviations from the mean value may have different causes, e.g. artifacts, extrasystoles or missing RR detections. Also cyclic changes in the RR intervals like sinus arrhythmia could be detected (Figure 5).

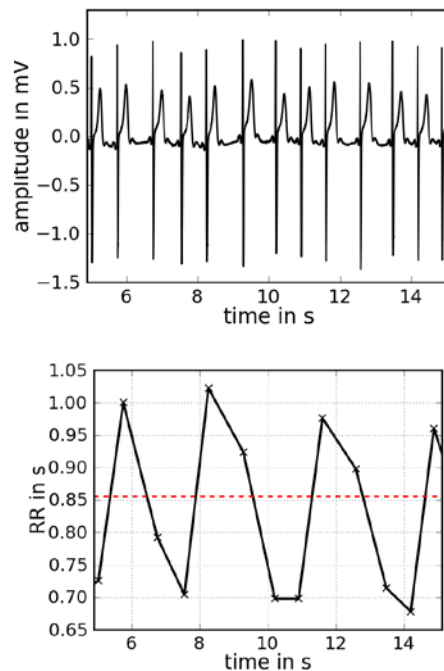


Figure 5. ECG stream with sinus arrhythmia and the corresponding tachogram.

## 4. Discussion and conclusion

The pediatric ECG database provides an instrument for the development and assessment of arrhythmia detection algorithms in AEDs for children younger than 9 years.

We determined the power line interferences and the signal and noise amplitudes. The results of the analysis gave information about the quality of the ECG streams. So we were able to identify signal intervals with good quality to form the final database. Additionally the dataset contains annotations of classified QRS complexes and medical annotation by a cardiologist for the whole ECG.

The ECG data will be divided into a public test dataset for the development of new algorithms for AEDs and an independent validation dataset. The validation dataset remains hidden and will not be published to evaluate the performance of new arrhythmia detection algorithms.

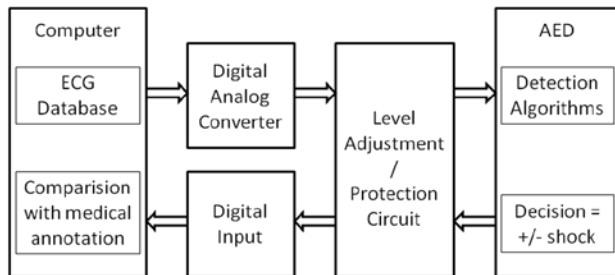


Figure 6. Block diagram of the electrical interface.

For the evaluation of the arrhythmia detection algorithms we will develop an electrical interface to AED devices (Figure 6). The interface should also reproduce the electrical characteristics of a patient. So the digital ECG stream from the database must be converted into an analog signal with level adjustment. At the same time, the interface should also reproduce the impedance of the patient. A galvanic isolation is required for protection of the ECG source against high voltage. The control computer is also equipped with a digital input card where the shock decision of the AED is monitored. The decision shockable/non-shockable of the AED will be automatically compared to the annotation of the ECG in the database.

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