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CHARACTERIZATION OF MATERNAL AND FETAL HEART RATES SIGNALS FOR IMPROVED TELEMETRY OPERATION

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Abstract

The importance of telecommunication systems in the medical field is immense especially as it relates to monitoring of cardiovascular conditions as well as taking the heart beat rate of expectant mothers and that of the fetus. Fetal monitoring during pregnancy enables the physician to diagnose and monitor pathological conditions especially asphyxia. The Electrocardiogram (ECG) is the simplest non-inversive diagnostic method used to solve various heart diseases. In this study, the use of Poisson probabilistic algorithm is employed to predict R-R intervals (a valid and reliable assessment of the time between two successive heartbeats, measured in milliseconds, and it is the most crucial for a scientific and practical use of HRV) in both maternal and fetal ECG signals for a set of 72 ECG heart rates for both the mother and her fetus. The application of Poisson technique has demonstrated promising results in error rates and better monitoring accuracy. 72 ECG signals for a certain R-R timing ranging from 0.66 to 0.99 in seconds were done, and ECG monitoring for important performance metrics, such as throughput, packet loss, error rate, and energy consumption was recorded. Using the Poisson forecast, a '*P*' error amplitude ranging from 0.7735 eV to 1.305 eV for an R-R timing of 0.66 to 0.99 sec was obtained. From the results, the eV error amplitude proves to be more error

Keywords and phrases: electrocardiogram, amplitude adaptive, WSN, throughput, BER diagnostic, non-inversive, pathological.

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prone from the ECG graphs obtained when compared with that of the actual data for Fetal Electrocardiogram (FECG) and Mother Electrocardiogram (MECG). The results from the research work compete favourable when compared with the wireless network error rate, throughput, energy consumption and energy efficiency, with and without the Poisson forecast. The proposed model in the work was also compared with an energy efficient wireless network system that applied Poisson algorithm to substantiate the effectiveness and accuracy of our system.

Abbreviations

FHR	:	Fetal Heart Rate
MECG	:	Mother Electrocardiogram
ECG	:	Electrocardiogram
FECG	:	Fetal Electrocardiography
AECG	:	Abdominal Electrocardiography
abfECG	:	Abdominal Fetal and Maternal Electrocardiograph
PPG	:	Photoplethysmogram
HRV	:	Heart Rate Variability
SDNN	:	Standard Deviation of Normal to Normal
WSN	:	Wireless Sensor Network
MHR	:	Maternal Heart Rate
QRS complex	:	Q-wave, R-wave, S-wave
R-R	:	R-wave to R-wave intervals

1. Introduction

There has been little development in fetal electronic heart rate monitors since the introduction of digital processing in the early 1980s. The transducers and processing algorithms used to detect the Fetal Heart Rate (FHR) have undergone little evolutional, though there has been an increase insensitivity and error signal. One possible outcome of the increased sensitivity of the Doppler transducer and the complex algorithms for extracting the FHR is the confusion of the heart rate between the mother, fetus and other acts when the fetal signal is poor. Ultra sound itself is high frequency sound that is beamed into the maternal abdomen using a transducer and held in place using a belt. The high frequency sound waves are then scattered by these cells or reflected off the fetal heart valves and other structures (e.g., the heart walls and blood vessels). Some of this scattered and reflected energy is detected by the transducer. If the ultra sound reflected from a moving structure, then it will undergo a change in frequency, called the *Doppler shift*. It is the change in frequency between the transmitted and reflected signals that can be heard from the monitor loudspeaker.

2. Literature Review

Abdominally detected fetal ECG heart rate monitoring was first described by Cremer in 1906. Advances in this area have led to new technologies that are capable of obtaining a clinically useful noninvasive abdominal fetal ECG along with the maternal ECG. In order to compare the maternal and fetal heart rates simultaneously, the Abdominal Fetal and Maternal Electrocardiograph (abfECG) was used. Figure 1 shows the electrodes attached to the mother's abdomen and the monitor. The abfECG monitor calculates the MHR as well as the FHR simultaneously. It uses the height and the width of the QRS complex (electrical activation of the ventricles of the heart), both of which are linked to the size of the heart to differentiate between the fetal and maternal heart signals.

Figure 1. Abdominal maternal and fetal ECG monitor (Practice [5]).

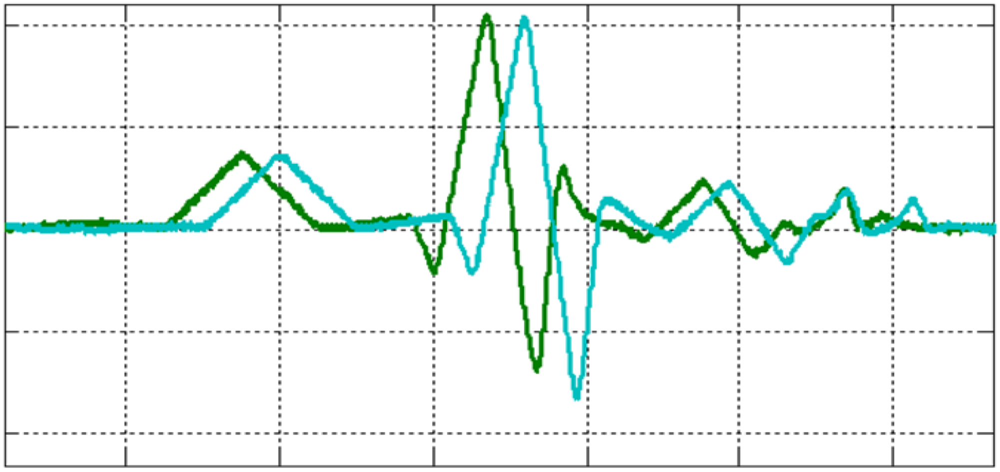

Figure 2. Raw fetal and maternal abdominal electrophysiological data.

The fetal width is always below 60 milliseconds and the maternal QRS is greater than 60 milliseconds in adults who have no unusual underlying cardiac pathology. Figure 2 demonstrates a typical electrophysiological data recorded by the monitor from the maternal abdomen before MHR and FHR hearts are calculated. Once the maternal ECG is identified, a template of the QRS complex is built up and then subtracted from the electrophysiological signal to leave the fetal QRS complex as shown in Figure 3. The upper part of the diagram shows the raw fetal and maternal signal, here the markers indicate a fetal heart signal. The lower part of the diagram shows the fetal ECG once the maternal ECG is subtracted. The RR interval is used to calculate the MHR and FHR from their respective signals.

In Andy [1], the authors focus on optimizing the quality of ECG sensor data so that the accompanying algorithm can return accurate fetal heart rate possible, which includes providing a powerful microcontroller for the algorithm to compute on and incorporating Photoplethysmogram (PPG) data to help identify ECG peaks (which are vital to finding heart rate) that may otherwise have not been detected. Components for this system were selected to have a balanced tradeoff between sensor accuracy (to capture ECG and PPG at reduced voltages due to abdominal placement) and power conservation (to minimally utilize the PPG and reduce energy during wireless transmissions). Since 1980 (Solum [7]), abdominal electrocardiography has been available as optional equipment on cardiotocographs. Besides phonocardiography and ultra-sound cardiographs, it is one of the methods for indirect cardiography. To allow calculations of the instantaneous fetal heart rate, the trigger pulse must have a constant quality, for instance, the R-wave in the ECG complex. This is obtained from indirect cardiography via the scalp electrode. In abdominal electrocardiography, the trigger pulse is the fetal R-wave as indirect electrocardiography which makes a registration of the instantaneous fetal heart possible. However, the maternal ECG complex will also be recorded and interfere with the fetal ECG-complex. When this happens, a substitution for the fetal complex is made in the cardiotocograph allowing a continuous recording of the fetal heart rate. The aim of this work is to investigate the agreement between direct and abdominal fetal electrocardiography, to calculate the frequency of substituted fetal heart beats by abdominal electrocardiography and to compare short term variability and long term variability recorded by direct and abdominal fetal electrocardiography.

In a similar context, Reza and Gari [6] review different recording and signal processing techniques for fetal ECG analysis that have been developed over the last forty years, and discuss both their short comings and advantages. Before doing so, they review fetal cardiac development, and the etiology of the fetal ECG. A selection of relevant models for the fetal/maternal ECG mixture is also discussed. In light of current understanding of the fetal ECG, we then attempt to justify recommendations for promising future directions in signal processing, and database creation.

3. Methodology

There are two different approaches to forecasting HRV measurements, one is the count data technique, while the second is the adaptive filter technique using MATLAB/Simulink. The count data model represents the core novel contribution to forecast HRV measurements whereas the adaptive filter technique using MATLAB/Simulink is used for comparison. The count datasets used for the forecast are done on an Excel sheet, while the ECG monitoring and adaptive filtering approach is done by the MATLAB program. The two datasets used for the experiment are the forecast dataset and the actual datasets from the MHR and FHR ECG. The forecast results on the MHR were also used to forecast the FHR dataset (Dawood and Allami [2]). In addition, the proposed methods were tested in MATLAB based on models of fetal and cardiotocography ECG sensor.

Time domain and frequency domain evaluations represent the most common linear methods for HRV analysis. Time domain measurements rely on statistical methods, and frequency domain measurements depend on power spectrum density (Kleiger et al. [4]). Due to the sophistication of the heart control function, it is unlikely that HRV can be entirely explained using linear techniques. Consequently, many nonlinear techniques have been used to identify the properties of the beat-to-beat variability (Gronwald et al. [3]). The next section illustrates linear (time and frequency domain) and nonlinear (e.g., entropy methods) HRV measurements.

3.1. Poisson distribution

The Poisson distribution is a single parameter discrete probability distribution that takes positive integer numbers. It is appropriate for applications that include the counts of events that occur randomly in a given interval of time, such as distance, area or other dimensions (Verdurmen [8]). Equation (1) describes the Poisson distribution where X is the number of events in any given interval, and λ is the mean number of events per interval. The probability of observing x events in a given interval is given by equation (1):

$$P(X = x) = e^{-\lambda \frac{\lambda^x}{x!}}, \quad x = 1, 2, 3, 4, \ldots, \infty. \tag{1}$$

3.2. Modeling a heartbeat case in Poisson

Consider a heartbeat rate ranging from $a \geq x \geq b$ beats per minute, therefore for $n_{\text{intervals}}$ of the heartbeat from $n, n+1, n+2, n+3 \cdots + n + \infty$, we consider the iteration with sum of possible outcomes, e.g.,

$$\begin{aligned} &nP(X = x); \\ &(n+1)P(X = x+1); \\ &(n+2)P(X = x+2); \\ &(n+3)P(X = x+3)\cdots \\ &(n+n)P(X = x+n). \end{aligned} \tag{2}$$

X in equation (2) refers to the number of RR data occurrences for 2 minutes and λ refers to the mean of RR intervals over specific period. In this study, the raw frequency counts from two minutes were filtered through a Poisson distribution in order to predict the five minutes frequency counts for a past ECG data. The Poisson filter is applied through estimating the parameters of the distribution from the data, calculating the probability distribution and multiplying the probability distribution by the number of observations. Indeed, the Poisson probability plays a critical role in forecasting of the RR frequency counts for a five-minute period from the counts from the first two minutes.

3.3. RR data forecasting technique

As the standard mean and Standard Deviation of Normal to Normal data (SDNN) equations failed to calculate a probabilistic factor for forecasting from the Poisson model, the standard mean and SDNN equations were modified in order to calculate the probabilistic parameters efficiently from the Poisson model, as illustrated.

The traditional equation for the mean RR is given as:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n}. \tag{3}$$

For the purpose of this study, the modified mean count RR is given as:

$$\mu_m = \frac{\sum_{i=1}^{n} (\text{RR data}_i \times \text{Count RR data}_i)}{n}. \tag{4}$$

The traditional equation for SDNN is:

$$\mathrm{SDNN} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n-1}} \tag{5}$$

whereas the modified SDNN equation with count RR data is:

$$\mathrm{SDNN}_m = \sqrt{\frac{\sum_{i=1}^{n}((\mathrm{RR\ data}_i \times \mathrm{Count\ RR\ data}_i) - \mu)^2}{n-1}}. \tag{6}$$

The forecast equation given in (6) above is used to calculate the 5 minutes Poisson forecasting algorithm count for R-R data in Table 1 given the 2 minutes R-R counts and timing intervals.

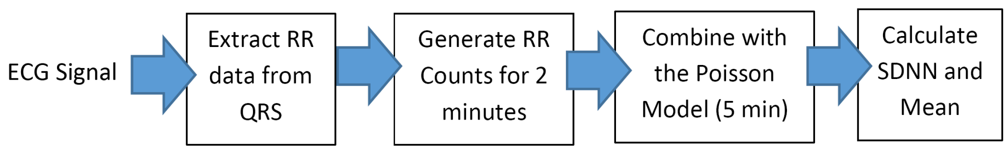

Figure 3. Three step Poisson forecasting for 3 minutes RR count.

The forecasting technique is implemented in three steps as illustrated in Figure 3. First, a real-time QRS detection data was applied to extract RR counts for two minutes. In the second step, the Poisson probability was applied to estimate the count of RR data at appoint in time three minutes later. In the third step, the two equations (5 and 6) were applied to calculate Standard Deviation of Normal to Normal data (SDNN) and mean, based on counted the R-R for a 5 minutes Poisson forecasting algorithm. The following algorithm in Table 1 is used to predict the five minutes SDNN and mean RR from two minutes RR count.

Table 1. Forecasting algorithm

Algorithm 1: 5 minutes Poisson forecasting algorithm
Input: Two minutes of ECG data
Output: Forecast SDNN and mean RR
Step 1: While ECG $\neq$ NDo
Step 2: Apply real-time Pan and Past QRS detection templates to extract RR data for two minutes
Step 3: Generate the count RR data (RR data count)
Step 4: Apply the Poisson probability to the RR counts in the RR data count to estimate the RR counts after another three minutes
Step 5: Combine the two-minute counted RR data count to the forecasted three-minute counted RR data to form the Poisson forecasted five-minutes RR data count
Step 6: Use equations in (4 and 6) to calculate mean and SDNN
Step 7: End while

4. Results and Discussion

The selected Key Performance Indicators (KPIs) that were discussed in the previous chapter will be thoroughly examined to ensure a proper analysis of the results. This section focuses on establishing a comparison between the performance of maternal and fetal ECG (chest ECG) under various network parameters. Table 2 depicts the data that was analyzed on the ECG-detected heartbeat synchronization between a mother and fetus, specifically recording the respiratory rates during labor from the 36th to the 41st week of pregnancy. Various datasets were collected, including the two-minute count RR data, Poisson forecasting count RR data, five-minute Poisson forecasting count RR data, and the five-minute RR data (actual RR data) for both the maternal and fetal prototypes.

Out of the 74 RR intervals, 16 RR data intervals were specifically selected and studied for a 5-minute count RR data, showcasing heartbeats with the same RR intervals. From the analysis of Table 2, it is evident that the ECG detection rates for the Poisson forecast and the actual data tend to decrease as the RR timing increases. However, it is noteworthy that the Poisson forecast exhibits a slightly higher success rate in monitoring compared to the actual forecast as depicted by the *P*-value. For instance, at 0.6 RR timing, the Poisson forecast shows a success rate of 0.980 for AECG, whereas the actual forecast stands at 0.961. Similarly, for FECG, the Poisson forecast demonstrates a successful monitoring rate of 0.915, while the actual forecast shows a rate of 0.907. This comparison highlights the effectiveness of the Poisson forecasting method in monitoring ECG data under different circumstances.

Table 2. Statistically analyzed MHR and FHR data

	Maternal heart rate (abdominal ECG)						Fetal heart rate (fetus ECG)					
RR timing	Two minute count RR data	Poisson forecasting count RRP-value	Actual count RRP-value	Five min Poisson forecasting count RR data	Five min RR data (actual RR data)	Electron volts (mV)	Two minute count RR data	Poisson forecasting count RRP-value	Actual count RRP-value	Five min Poisson forecasting count RR data	Five min RR data (actual RR data)	
0.6	1	0.98	0.961	2	2	3.68	2	0.915	0.907	3	3	0.95
0.64	1	0.977	0.954	2	2	3.66	2	0.912	0.9	3	3	0.93
0.66	17	0.975	0.951	29	28	3.64	31	0.91	0.897	54	52	0.91
0.68	51	0.973	0.948	87	85	3.62	94	0.908	0.893	162	157	0.89
0.69	11	0.973	0.946	19	18	3.61	20	0.907	0.892	35	34	0.88
0.69	57	0.973	0.946	98	95	3.6	105	0.907	0.892	181	176	0.87
0.71	77	0.971	0.942	132	128	3.58	142	0.905	0.888	245	237	0.85
0.73	58	0.969	0.938	100	97	3.56	107	0.903	0.884	185	179	0.83
0.75	27	0.967	0.935	47	45	3.54	50	0.901	0.88	86	83	0.81
0.77	53	0.965	0.931	92	88	3.52	98	0.899	0.876	169	163	0.79
0.79	23	0.963	0.927	40	38	3.5	43	0.897	0.873	74	71	0.78
0.81	8	0.961	0.923	14	13	3.48	15	0.895	0.868	26	25	0.75
0.83	2	0.958	0.919	3	3	3.46	4	0.893	0.864	6	6	0.74
0.85	5	0.956	0.914	9	8	3.44	9	0.891	0.86	16	15	0.71
0.88	3	0.953	0.908	5	5	3.42	6	0.887	0.854	10	9	0.69
0.91	2	0.949	0.901	4	3	3.4	4	0.884	0.847	6	6	0.67
0.93	1	0.947	0.897	2	2	3.39	2	0.882	0.843	3	3	0.65
0.98	1	0.941	0.886	2	2	3.36	2	0.876	0.831	3	3	0.63
1	1	0.939	0.881	2	2	3.34	2	0.873	0.827	3	3	0.61
1.13	2	0.922	0.851	4	3	3.32	4	0.857	0.796	7	6	0.59

1.38	2	0.89	0.792	4	3	3.3	4	0.824	0.737	7	6	0.56
1.48	1	0.877	0.769	2	2	3.28	2	0.812	0.715	4	3	0.55
1.65	4	0.856	0.733	8	7	3.26	7	0.791	0.679	14	12	0.53
1.67	2	0.854	0.729	4	3	3.24	4	0.788	0.675	7	6	0.51
1.71	2	0.849	0.721	4	3	3.22	4	0.784	0.667	7	6	0.49
1.74	2	0.846	0.716	4	3	3.2	4	0.78	0.661	7	6	0.47
1.77	1	0.843	0.71	2	2	3.18	2	0.777	0.656	4	3	0.45
1.8	2	0.839	0.704	4	3	3.16	4	0.774	0.65	7	6	0.43
1.82	3	0.837	0.701	6	5	3.14	6	0.772	0.647	11	9	0.41
1.85	4	0.834	0.696	8	7	3.12	7	0.769	0.641	15	12	0.39
1.87	3	0.832	0.692	6	5	3.1	6	0.767	0.638	11	9	0.37
1.89	4	0.83	0.689	8	7	3.08	7	0.765	0.635	15	12	0.35
1.92	4	0.827	0.684	8	7	3.06	7	0.762	0.63	15	12	0.33
1.96	4	0.823	0.678	8	7	3.04	7	0.758	0.623	15	12	0.31
1.99	2	0.82	0.673	4	3	3.02	4	0.755	0.619	8	6	0.29
2.4	1	0.791	0.626	2	2	2.98	2	0.726	0.571	4	3	0.27
2.63	1	0.781	0.611	2	2	2.93	2	0.716	0.556	4	3	0.25
2.77	1	0.778	0.605	2	2	2.91	2	0.713	0.551	4	3	0.24

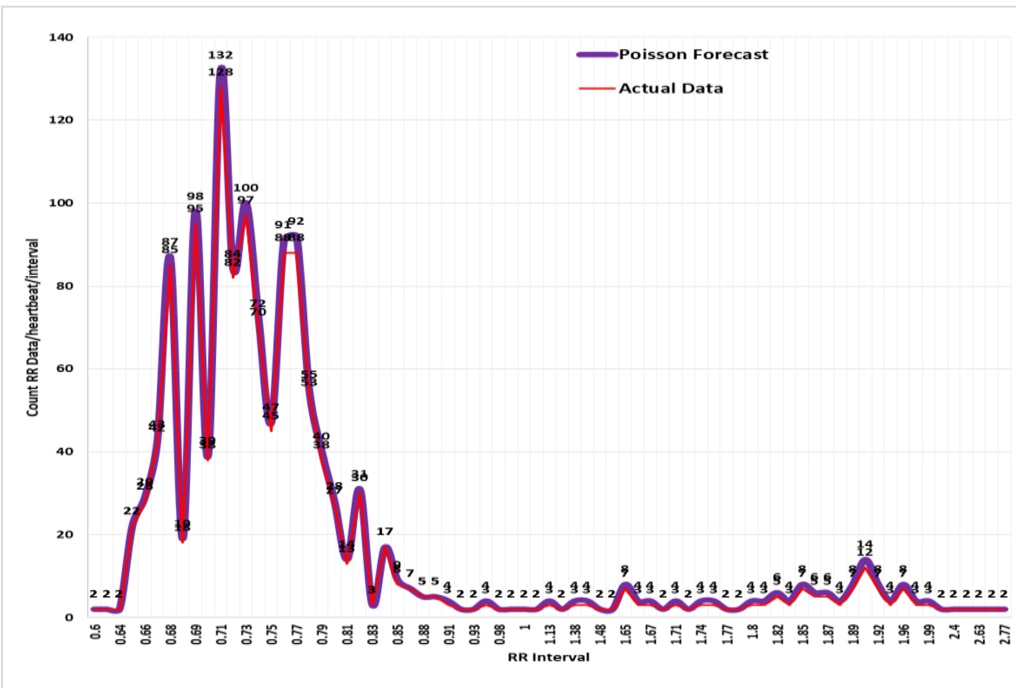

Figure 4. MHR count RR data for Poisson forecast and actual data.

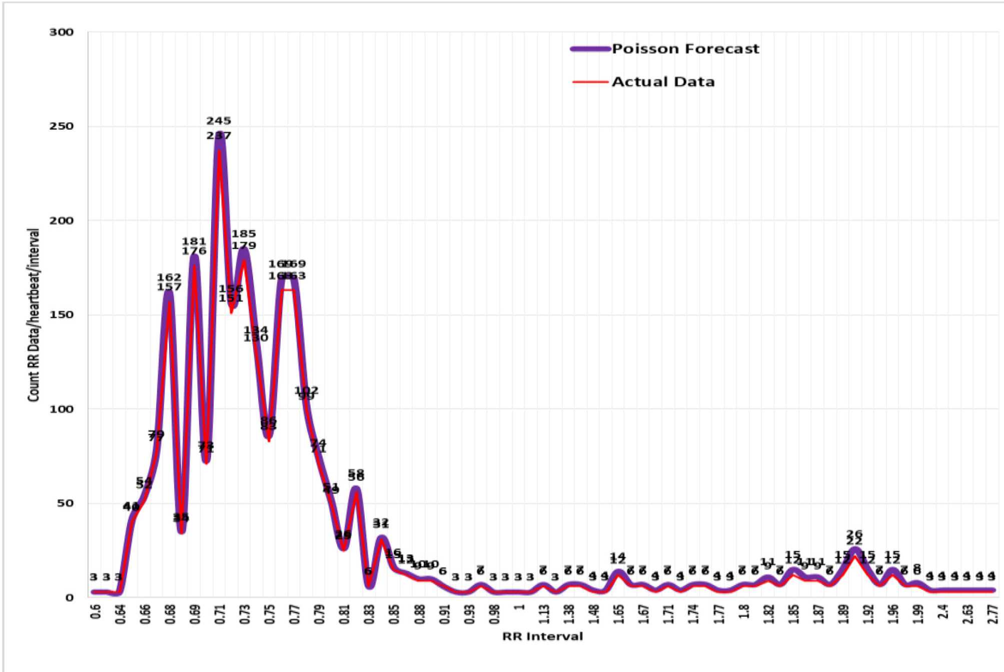

Figure 5. MHR count RR data for Poisson forecast and actual data.

Figures 5 and 6 illustrate the data on heartbeat/interval plots for both maternal and fetal ECG, specifically categorized by heartbeat per RR interval. It is important to state here that employing Poisson statistical analysis gives room for the possibility of selecting high counts during the MHR and FHR process, which improved the accuracy of estimating heartbeats for both maternal and fetal ECG processes during the implementation using filtering/cancellation techniques. For instance, utilizing the Poisson forecasting method resulted in predicting 29 counts RR data for the maternal ECG instead of the initial 28, and 54 count RR data for the fetal ECG instead of 52 within a 0.66 RR interval. Similarly, the Poisson forecast indicated 87 count RR data for the maternal ECG instead of 86, and 162 count RR data for the fetal ECG instead of 152 within a 0.68 RR interval.

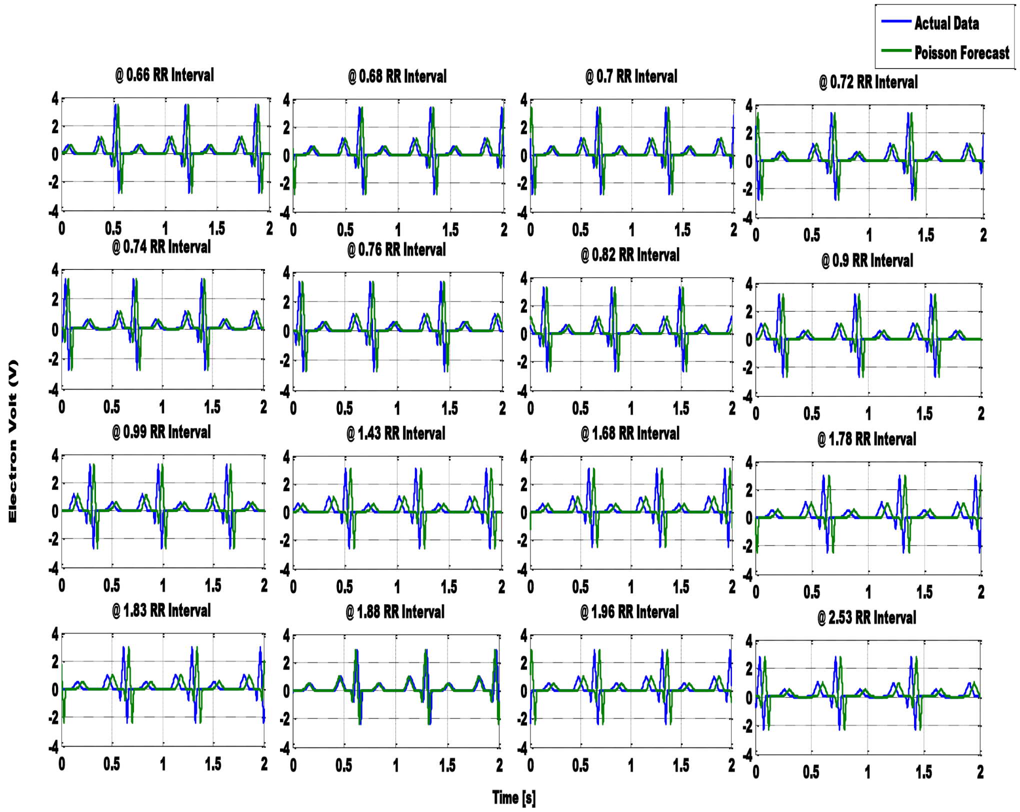

Figure 6. AECG complex for selected RR timings.

During visual assessment of results, we observed that the shapes of the Maternal Heart Rate (MHR) and Fetal Heart Rate (FHR) waveforms were very similar when determined based on the Abdominal Electrocardiography (AECG) and Fetal Electrocardiography (FECG), respectively. In Figure 6, we presented the AECG results for the MHR using selected RR timing. The comparison in figure revealed the AECG performance for the actual ECG recorded data and the Poisson forecast data. We utilized the Poisson statistical approach to predict and the ECG optimization model to enhance the timing parameters of the ECG complex. Our results showed that for all RR intervals, each timing parameter for the Poisson forecast led the actual timing data by +0.001, as indicated in Table 3. The estimated RR interval for the maternal heart rate in AECG was 0.43 seconds, with a 3 ECG spectrum in 2 seconds for both the actual and the Poisson forecast data.

There were no significant differences noted in the statistical measures of timing parameters of corresponding abdominal P-QRS-T complexes obtained using the Poisson statistical approach. All determined durations of particular events were comparable. Table 3 presents a summary of the AECG complex comparison for the Poisson forecast and the actual data.

Table 3. AECG summary table for ECG components

	P[s]		PQ[s]		QRS[s]		ST[s]		T[s]		RR[s]
	AD	PF	AD	PF	AD	PF	AD	PF	AD	PF	
0.66	.11	P + 0.03	.14	PQ + 0.029	.16	QRS + 0.03	.21	ST + 0.03	.12	T + 0.03	.674
0.68	.11	P + 0.031	.14	PQ + 0.03	.16	QRS + 0.031	.21	ST + 0.031	.12	T + 0.031	.674
0.7	.11	P + 0.032	.14	PQ + 0.031	.16	QRS + 0.032	.21	ST + 0.032	.12	T + 0.032	.674
0.72	.11	P + 0.033	.14	PQ + 0.032	.16	QRS + 0.033	.21	ST + 0.033	.12	T + 0.033	.674
0.74	.11	P + 0.034	.14	PQ + 0.033	.16	QRS + 0.034	.21	ST + 0.034	.12	T + 0.034	.674
0.76	.11	P + 0.035	.14	PQ + 0.034	.16	QRS + 0.035	.21	ST + 0.035	.12	T + 0.035	.674
0.82	.11	P + 0.036	.14	PQ + 0.035	.16	QRS + 0.036	.21	ST + 0.036	.12	T + 0.036	.674
0.9	.11	P + 0.037	.14	PQ + 0.036	.16	QRS + 0.037	.21	ST + 0.037	.12	T + 0.037	.674
0.99	.11	P + 0.038	.14	PQ + 0.037	.16	QRS + 0.038	.21	ST + 0.038	.12	T + 0.038	.674
1.43	.11	P + 0.039	.14	PQ + 0.038	.16	QRS + 0.039	.21	ST + 0.039	.12	T + 0.039	.674
1.68	.11	P + 0.040	.14	PQ + 0.039	.16	QRS + 0.040	.21	ST + 0.040	.12	T + 0.040	.674
1.78	.11	P + 0.041	.14	PQ + 0.040	.16	QRS + 0.041	.21	ST + 0.041	.12	T + 0.041	.674
1.83	.11	P + 0.042	.14	PQ + 0.041	.16	QRS + 0.042	.21	ST + 0.042	.12	T + 0.042	.674
1.88	.11	P + 0.043	.14	PQ + 0.042	.16	QRS + 0.043	.21	ST + 0.043	.12	T + 0.043	.674
1.96	.11	P + 0.044	.14	PQ + 0.043	.16	QRS + 0.044	.21	ST + 0.044	.12	T + 0.044	.674
2.53	.11	P + 0.045	.14	PQ + 0.044	.16	QRS + 0.045	.21	ST + 0.045	.12	T + 0.045	.674

Figure 7 presents the FECG results for the FHR for selected RR timings. The comparison plot shows the FECG performance for the actual ECG recorded data and the Poisson forecast data. For the FECG, the Poisson statistical approach has been used to predict and improve the timing parameters of the ECG complex as shown.

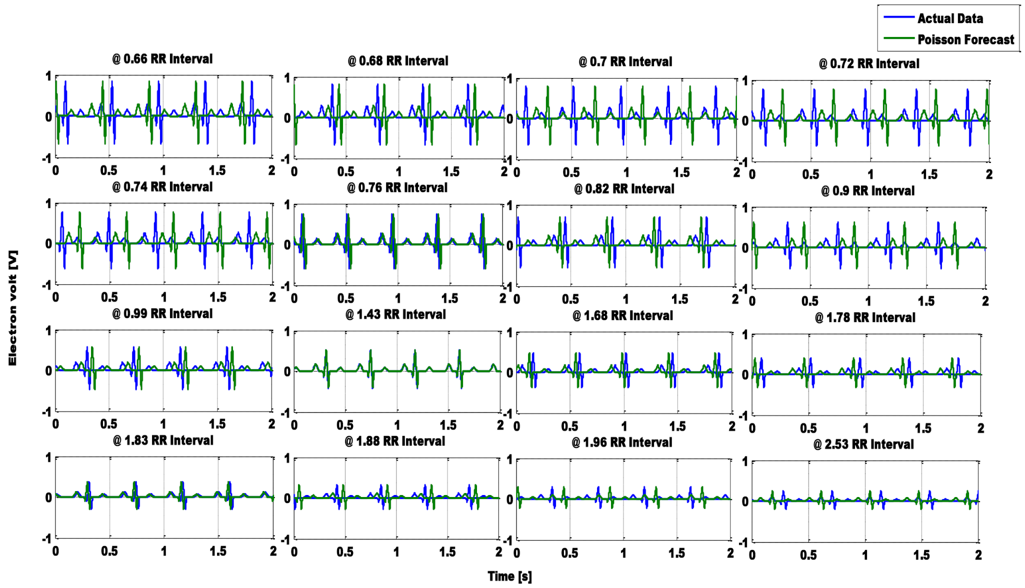

Figure 7. FECG complex for selected RR timings.

Table 4. FECG summary table for ECG components

	P[s]		PQ[s]		QRS[s]		ST[s]		T[s]		RR[s]
	AD	PF	AD	PF	AD	PF	AD	PF	AD	PF	.43
0.66	.07	P - 0.09	.08	PQ - 0.09	.02	QRS - 0.09	.07	ST - 0.09	.08	T - 0.09	.43
0.68	.07	P + 0.08	.08	PQ + 0.08	.02	QRS + 0.08	.07	ST + 0.08	.08	T + 0.08	.43
0.7	.07	P + 0.11	.08	PQ + 0.11	.02	QRS + 0.11	.07	ST + 0.11	.08	T + 0.11	.43
0.72	.07	P + 0.12	.08	PQ + 0.12	.02	QRS + 0.12	.07	ST + 0.12	.08	T + 0.12	.43
0.74	.07	P + 0.13	.08	PQ + 0.13	.02	QRS + 0.13	.07	ST + 0.13	.08	T + 0.13	.43
0.76	.07	P + 0.01	.08	PQ + 0.01	.02	QRS + 0.01	.07	ST + 0.01	.08	T + 0.01	.43
0.82	.07	P - 0.06	.08	PQ - 0.06	.02	QRS - 0.06	.07	ST - 0.06	.08	T - 0.06	.43
0.9	.07	P + 0.16	.08	PQ + 0.16	.02	QRS + 0.16	.07	ST + 0.16	.08	T + 0.16	.43
0.99	.07	P + 0.08	.08	PQ + 0.08	.02	QRS + 0.08	.07	ST + 0.08	.08	T + 0.08	.43
1.43	.07	P	.08	PQ	.02	QRS	.07	ST	.08	T	.43
1.68	.07	P - 0.03	.08	PQ - 0.03	.02	QRS - 0.03	.07	ST - 0.03	.08	T - 0.03	.43
1.78	.07	P - 0.04	.08	PQ - 0.04	.02	QRS - 0.04	.07	ST - 0.04	.08	T - 0.04	.43
1.83	.07	P - 0.01	.08	PQ - 0.01	.02	QRS - 0.01	.07	ST - 0.01	.08	T - 0.01	.43
1.88	.07	P + 0.11	.08	PQ + 0.11	.02	QRS + 0.11	.07	ST + 0.11	.08	T + 0.11	.43
1.96	.07	P + 0.15	.08	PQ + 0.15	.02	QRS + 0.15	.07	ST + 0.15	.08	T + 0.15	.43
2.53	.07	P - 0.15	.08	PQ - 0.15	.02	QRS - 0.15	.07	ST - 0.15	.08	T - 0.15	.43

5. Conclusion and Recommendation

This paper carefully characterized the performance of the MHR and FHR signals in the detection of the fetal heart rate. A thorough examination and monitoring system within the context of maternal and fetal heart rate monitoring underscores the critical nature of precise data collection and processing for ECG records, as depicted in this study. Additionally, the utilization of the Poisson distribution for predicting RR intervals in both maternal and fetal ECG signals has shown promising outcomes in reducing error rates and enhancing monitoring accuracy. The results presented gave a summary of an accurate analysis for the fetal heart rate based on the characteristics of the MHR and FHR signals, and it can be deduced that the application of the Poisson forecast algorithm will initiate accurate detection of MHR and FHR signals during fetal heart rate detection.

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