Heart Rate Variability Enhances the Accuracy of Non-invasive Continuous Blood Pressure Estimation Under Blood Loss

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Research

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Heart rate variability enhances the accuracy of non-invasive continuous blood pressure estimation under blood loss

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Abstract

Background: To propose a new method for real-time monitoring of human blood pressure under blood loss (BPBL), this article combines pulse transit time (PTT) and heart rate variability (HRV) as input parameters in order to establish a model for the estimation of BPBL.

Methods: Effective parameters such as PTT, R-R interval (RRI), and HRV were extracted and used to establish the blood pressure (BP) estimation. Three BP estimation models were established: the PTT model, the RRI model, and the HRV model, and they were divided into experimental group and control group. Finally, the effects of different estimation models on the accuracy of BPBL estimation were evaluated based on the experimental results.

Results: The Pearson correlation coefficients R were 0.7731, 0.8943 and 0.9169 for the PTT model, the RRI model, and the HRV model, respectively. The root means square error of the estimation set (RMSEP) were 16.83 mmHg, 11.87 mmHg and 10.59 mmHg, respectively.

Conclusion: The results suggest that the accuracy of the BPBL estimated by the RRI and HRV models is better than that of the PTT model, which means that both RRI and HRV can enhance the accuracy of BPBL estimation, and HRV seems to be more effective in improving the accuracy of BP prediction compared to RRI. These results provide a new idea for other scholars in the field of BPBL estimation research.

Key words: cuff-less blood pressure, pulse transit time, partial least squares, HRV

1 Background

2 Hemorrhagic shock constitutes the most common cause of death in patients who die at the scene of an accident or battlefield
3 [1-3], it is the leading cause of potentially preventable death among trauma patients [4,5], and generally, it also can have

4 extremely serious consequences or even can be fatal [6-8]. The blood pressure (BP) of the human body changes rapidly during
5 blood loss which cannot be monitored dynamically [8], hence, it will greatly affect the timely judgment of the condition and
6 the effect of any treatment provided. Therefore, it is important to establish a non-invasive, fast, simple, and effective method
7 of BP estimation to monitor its change under blood loss. However, on the global level, there is still a large gap in the related
8 research in this field.

9 When BP decreases due to blood loss, cardiac sympathetic and parasympathetic nerves accelerate the blood circulation
10 and increase the BP through spontaneous regulatory actions. Therefore, the monitoring of cardiac autonomic nerve regulation
11 will help improve the accuracy of BP estimation. Heart rate variability (HRV) reflects several aspects of cardiac autonomic
12 nerve activity and is one of the most important indicators of cardiac autonomic nervous regulation [9-11]. Therefore, this
13 study combines HRV and the existing pulse transit time (PTT) theory to establish a novel BP estimation model, which is
14 able to provide continuous and efficient.

15 Compared with the traditional BP measurement method, the PTT method has attracted great attention in recent years
16 because of its advantage of being a non-invasive, continuous, and cuff-less BP measuring method. Much research has been
17 conducted on the method of estimating the BP based on PTT. Wong et al. [12] and Gesche et al. [13] have shown that the
18 systolic BP (SBP) highly correlates with PTT, which also verifies the feasibility of predicting BP values based on PTT.
19 Gesche et al. [13], Huynh et al. [14], and Mukkamala et al. [15] have provided the formula for calculating the BP value based
20 on PTT and proved the reliability of the method. Ding et al. [16], Tao et al. [17] and Liu et al. [18] have adopted different
21 methods to optimize the PTT method as well as improve the accuracy of predicting BP values. In addition to the theoretical
22 research, Zheng et al. [19] applied the PTT method to continuously monitor BP at night and verified its feasibility for the
23 continuous monitoring of BP. Others used the PTT method in personal health care to continuously measure human BP [20],
24 they combined the PTT method with a chest sensor and performed a Mean arterial pressure (MAP) estimation on the chest
25 through a corresponding calibration strategy [12], or used the PTT method to measure BP during and after dynamic exercise

26 [21] which have all yielded in favorable results.

27 Although much research has been conducted which has yielded in a series of significant results in this field, there are still
28 some certain limitations in current research outputs. Firstly, there is a large gap in the estimation and analysis of BPBL in
29 terms of accuracy. Given that the scenario of blood loss is very common in the clinic, continuous monitoring and early
30 warning of decreasing BP in the case of blood loss is important, which is what currently is lacking in the relevant BP research.
31 In addition, there are still differences in the PTT-based BP estimation methods which are tied to individual patients, leading
32 to a decrease in the accuracy of the results. Unfortunately, because the physiological states are not exactly the same and its
33 effects cannot be completely eliminated in different individuals, their estimated BP will be different, hence, a standard
34 continuous BP measurement method that is suitable for most people may be difficult to achieve.

35 In this article, R-wave to R-wave interval (RRI) and HRV will be used as input feature parameters to establish the BP
36 estimation model. RRI and HRV are common indicators to measure the physiological status of different individuals, and,
37 when used as input parameters to establish the BP estimation model, the errors caused by individual differences can
38 effectively be reduced and the accuracy of BP estimation can be improved. This study uses RRI and HRV to establish
39 different BP estimation models and evaluates each model based on experimental results, exploring the impact of different
40 input parameters on the accuracy of BP estimation under blood loss. The results of this study may be helpful for other people
41 who are conducting BP estimation research, and it is hoped to provide an additional contribution to the development in this
42 field.

43 **Methods**

44 **Basic theory of blood loss**

45 When blood loss occurs, the blood volume in the blood vessels decreases, which in turn causes the BP to decrease. At the
46 same time, the decrease in BP will be fed back to the nerve center, initiating a series of adjustment activities to increase BP,
47 including accelerated blood pumping to increase cardiac output and blood vessel contraction. In order to better estimate the

48 changes of BPBL, the physiological changes of the human body during blood loss were analyzed, and parameters closely
 49 related to blood loss were determined in order to estimate BPBL.

50 Photoplethysmography (PPG) is the most common pulse wave monitoring technology, which can detect pulse wave changes during
 51 the physiological changes of the human body. As shown in Fig. 1 [22], the PPG waveform includes alternate components (AC) and
 52 direct components (DC) [23]. AC is depending on the heart rate, and is the pulsating component of the PPG waveform, which
 53 superimposes on the DC component [23]. The DC component is related to the blood volume in the blood vessel, and will slowly change
 54 due to respiration and changes in the diameter of the blood vessel.

55
 56 Fig. 1. Basic theory of blood loss.

57 Since there is a certain functional relationship between the total blood volume V of the venous blood (V_{ven}), the arterial blood (V_{art})
 58 and the blood vessel diameter L , it is assumed that the following formula exists between them:

59
$$V = V_{ven} + V_{art} \quad (1)$$

60
$$V_{art} = V(DC) + V(AC) \quad (2)$$

61
$$L = f(V) \quad (3)$$

62 When blood loss occurs, the blood volume in the blood vessel decreases, and according to formula (3), the blood vessel diameter L

will also decrease. Due to the change in diameter L , the static arterial blood (DC) component of the PPG waveform will also change. At the same time, the heart will speed up when blood is lost, trying to maintain enough blood supply to the organs, which will change the heart rate. Since AC is determined by heart rate, it will also change significantly during the blood loss process. For the estimation of BPBL, the AC and DC parameters that are closely related to blood loss are of significance. Therefore, in this study the two parameters AC and DC were extracted for the construction of the BPBL model. In addition, since the human body performs autonomous neuromodulation to suppress BP reduction during blood loss, the quantification of the neuromodulation process will help improve the accuracy of the BPBL estimation. One method of assessing autonomic modulation is through HRV, which is usually calculated by RRI and is a common method for monitoring autonomic nerve activity [10-11]. In this study, the time domain parameters (SDNN and RMSSD) and the frequency domain parameters (HF) are used to measure the HRV. Therefore, in addition to AC and DC, RRI and HRV signals were also extracted and utilized to estimate the BPBL.

Fig. 2. Experimental scene diagram.

Experimental process

In this study, Landrace pigs were used as experimental objects. They were fixed on the operating table and anesthetized during the experiment. As shown in Fig. 2, three signals were detected during the experiment: the first signal was the ECGs signal detected around the heart, which was obtained via the unipolar lead method. The second signal was the pulse signal located at the nose, which was obtained via the PPG method. The third signal was the invasive continuous blood pressure

80 (IBP) located in the left femoral artery of the pig. IBP is regarded as the gold standard for BP measurement and can be used
81 for modeling calculations and verification. All three signals were collected from the pigs simultaneously and were displayed
82 by the Chengdu Instrument RM6240C multi-channel physiological signal acquisition system, with experimental data being
83 recorded throughout the process, and all signals being sampled at 1000 Hz.

84 The experiments were conducted on a total of five pigs with a weight range of 31 ± 8.5 kg. The specific experimental
85 process is shown in Fig. 3. At the beginning of the experiment, it was crucial to record the baseline physiological data of the
86 pigs in a stable state. It was made sure the pigs were under anesthesia, and 200ml of blood was withdrawn via the pigs'
87 carotid artery. The corresponding time points were recorded and the physiological changes of the pigs were observed. When
88 the BP and HR of the pigs reached a relatively stable state, the pigs were bled again (200ml-400ml) and the corresponding
89 data were recorded. As soon as the pigs lost blood at a certain level, they were given another blood transfusion. The above
90 process was repeated several times, with the number of repetitions determined according to the specific experimental
91 situations. Because the blood volume of the pigs is in linear relationship with their body weight, the number of the
92 bloodletting instances was determined according to the weight of the pigs and the specific experimental conditions, in order
93 to achieve the aim of this study. For this study, a total of 10 sections of valid blood loss data were extracted during the
94 experiment.

95
96 Fig. 3. Introduction to the experimental process.

97 Feature parameter extraction

98 After the experiment, the main characteristic parameters such as PTT, RRI, and HRV were extracted from the ECG and PPG
99 signals collected from the experiments. As shown in Fig. 4 (a), The PTT refers to the time that the pulse wave travels from the

100 heart to the surrounding branch blood vessels during the pumping of the heart. In this study, PTT was regarded the time of
 101 the pulse wave traveling from the heart to the pig's nose.

102 The acquisition process of PTT was as follows: First, the peak position of the ECG signal and the PPG signal with the
 103 corresponding algorithm was located. Due to the ECG and PPG signals being collected simultaneously, and the pulse wave
 104 signal being transmitted from the heart to the pig's nose, the ECG signal preceded the PPG signal for a period of time, and
 105 there was only one PPG peak between two adjacent R peaks. In the same way, all the data segments that met these criteria
 106 were extracted, and the remaining data points were regarded as outliers and discarded. After all the valid data segments were
 107 obtained, the R peak point of the ECG signal was used as the starting point, and the peak point of the adjacent PPG signal
 108 was used as the endpoint. The time between the starting points and the endpoints is the pulse wave transit time, and all PTT
 109 data were extracted to establish the BPBL estimation model.

110 (a)
 111 (b)
 Fig.4. The extraction of PTT, AC, and DC.

112 In addition to the PTT parameters, other characteristic parameters were also extracted to establish the BPBL estimation
 113 model. As shown in Fig. 5, these parameters include two parts: the first component is the pulse amplitude (AC) and peak
 114 (DC) extracted from the PPG signal. AC/DC as the input parameter was also calculated to reduce the interference of
 115 individual differences. The second component is the RRI and HRV (SDNN, RMSSD, and HF) extracted from the PPG signal,
 116 which is the key parameter of this experiment. Combined with PTT and PTT/ RRI, a total of nine characteristic parameters
 117 were extracted in the study which were mainly used as input parameter to establish the BPBL estimation model.

Fig. 5. Parameters for estimating BPBL

Construction of the BPBL estimation model

Because the BP estimation model constructed in this study has multiple input parameters which show a strong correlation between each other, the partial least squares (PLS) method was deemed suitable to build a BP estimation model under blood loss. In this study, three BP estimation models were constructed: the PTT model, the RRI model, and the HRV model. The PTT model refers to a commonly used BP estimation model based on PTT, and the input characteristic parameters included PTT, AC, DC, AC/DC. The RRI model and the HRV model refer to the model constructed by adding the RRI and the HRV, respectively, based on the input parameters of the PTT model. In the described experimental procedure of this study, the PTT model was set as the control group, while the RRI model and the HRV model were set as the experimental group. The estimation accuracy of different BP estimation models was compared to evaluate the advantages and disadvantages of the different models and the influence of the two characteristic parameters RRI and HRV on the BPBL estimation accuracy. The input characteristic parameters of the different models are shown in Table 1.

Table 1. Comparison of Input Parameters of Different Models

BPBL Model	Input Parameters
PTT model	PTT, AC, DC, AC/DC
RRI model	PTT, AC, DC, AC/DC, RRI, PTT/RRI
HRV model	PTT, AC, DC, AC/DC, SDNN, RMSSD, HF

When constructing the model, the 1229 data samples obtained from the experiment were divided into two components,

133 the training set and the estimation set. The training set and the estimation set accounted for 9/10 and 1/10 of the total sample,
134 respectively. After every nine data sets in the total sample, one data set was selected to form the estimation set, and the
135 remaining data was allocated to the training set. In this study, PLS was used to establish a model between 1107 samples and
136 the SBP values in the training set. Then the established training model was used to estimate the SBP values of 122 samples
137 in the estimation set.

138 The correlation between the estimated value and the actual value was established by evaluating the predictive ability of
139 the model through the following indicators: the root means square error (RMSEC) and the correlation coefficient of the
140 training set (R_t), and the root mean square error (RMSEP) and the correlation coefficient of the estimation set (R_e).
141 When the correlation coefficient is larger and the root mean square error is smaller, it indicates that the model has a better
142 predictive ability.

143 **Results**

144 In the experiment, three different BPBL estimation models were constructed with the input feature parameters mentioned
145 previously based on the partial least squares (PLS). Three different BPBL estimation models were tested with the same
146 experimental data, and the experimental results of the training set and the estimation set of SBP under blood loss were
147 obtained. There were 1229 sample points of all models. The P-values in table 2 shows that all experimental results were
148 statistically significant. The detailed experimental results of each model were shown in Table 2 and Fig. 6.

149 The correlation coefficient (R_p) and the root mean square error (RMSEP) were calculated in our study to assess the
150 accuracy of the estimated BPBL values. According to the Table 2, the Pearson correlation coefficient of the SBP and IBP
151 estimated by the PTT model of the experimental group, was lowest with 0.77 ($P<0.01$), while the Pearson correlation
152 coefficients estimated by the RRI model and the HRV model of the experimental group, reached 0.89 ($P<0.01$) and 0.92
153 ($P<0.01$), respectively. In addition, the root mean square error of the test set in the PTT model was the largest with 16.83,
154 while the mean square error of the estimation set in the RRI model and the HRV model was 11.87 and 10.59 respectively.

155

Table 2. Comparison of experimental results of three models.

Blood Loss Model	Optimal Factor	Rt	RMSEC	Rp	RMSEP	P-value
PTT model	3	0.73	18.1 mmHg	0.77	16.8 mmHg	***
RRI model	5	0.89	12.2 mmHg	0.89	11.9 mmHg	***
HRV model	6	0.91	11.1 mmHg	0.92	10.6 mmHg	***

156

157

*** represents $P < 0.01$. Rt and Rp represent the Pearson correlation coefficients of the training set and prediction set, respectively. RMSEC and RMSEP represent the root mean square error of the training set and prediction set, respectively.

158

159

Fig. 6. The results of the training set and prediction set of three blood loss models

160

161

Therefore, it is obvious that the correlation estimated by the RRI model and the HRV model is better than that of the PPT model. Moreover, the estimated effect of the BP value of the HRV model is greater than that of the RRI model.

162 The results indicate that the ordinary PTT method is not accurate in estimating BPBL, and cannot be used directly in
 163 BPBL estimation. In addition, we also can find that both RRI and HRV are closely related to BPBL, and they are of great
 164 help in improving the estimation accuracy of BPBL values. And the results also provide further guidance for the study of
 165 BPBL based on PTT and HRV.

166 Discussion

167 The purpose of this study was to estimate the BPBL non-invasively and continuously based on the HRV, PTT, and other
 168 parameters. In order to achieve this purpose, an experimental group and a control group were established together with three
 169 estimation models. The effect of the estimation models was evaluated through experimental results and the impact of
 170 different feature parameters on the accuracy of the BP estimation was explored.

171 (a) (b) (c)
 172 Fig. 7. Bland-Altman plot of the difference between actual SBP and estimated SBP in three models.

173 The experimental group has a better effect on BP estimation

174 Compared with the control group, the correlations of the RRI model and the HRV model increased by 10.1% and 18.6%,
 175 respectively. At the same time, compared with the PTT model, the mean square error was reduced by 29.5% and 37.1%,
 176 respectively. Therefore, it is obvious that the experimental group achieve a much better accuracy than the control group.

177 In addition, compared with the control group, parameters related to RRI and HRV were added in the experimental group
 178 respectively, however, the results showed great differences between the two groups. The result suggests that both the RRI
 179 and the HRV have an enhanced effect on the accuracy of the BPBL estimation, and the enhancement effect is significant

180 when HRV and R-R intervals are added as input parameters. It could be speculated that this is due to HRV and R-R intervals
181 being more relevant to the characteristics of the human body, and when used as input parameters to establish the estimation
182 model they may reduce the impact of individual differences and increase the accuracy of BP estimation.

183 **HRV Enhances the Accuracy of BPBL Estimation**

184 According to the experimental results, the HRV model has the highest correlation and the smallest root mean square error, which
185 suggests that HRV greatly promotes the prediction accuracy of BPBL. As already mentioned in the second part of this article,
186 when the BP of the human body decreases, a series of adaptations occurs in the cardiac neuromodulation center to raise the
187 BP, including accelerated blood pumping and blood vessel contraction until the BP rises and eventually becomes stable.
188 Neuromodulation plays a very important role in the process of blood loss, and HRV is one of the important indicators for
189 clinical monitoring of cardiac autonomic nerve activity. From the results of this study it can be concluded that HRV has a
190 strong correlation with BP changes during blood loss, which when used as an input feature parameter to model BPBL, the
191 results will be the most precise among the three models and much higher than the PTT model. Furthermore, HRV can
192 significantly enhance the estimation accuracy of BPBL.

193 **HRV is more meaningful than RRI**

194 By comparing the estimation results of the RRI model and the HRV model of the experimental group, the Pearson correlation
195 coefficient of SBP and IBP estimated by the HRV model is higher than that of the RRI model, and the mean square error of
196 the estimated value of the HRV model is lower than that of the RRI model. This shows that HRV has a better correlation
197 with BPBL, and can greatly enhance the accuracy of BPBL estimation.

198 The HRV indicators used in this study are calculated by RRI, since RRI may contain more information than HRV, such as
199 heart rate. However, the comparison of the two models in the experimental group indicated that HRV is better than RRI in
200 estimating the BPBL. Therefore, it can be argued that when blood loss in pigs occur, they mainly regulate it through the
201 nervous system, and HRV is more closely related to the nervous system than the RRI. In addition, compared with RRI, HRV

provides a more effective extraction of blood loss information and largely removes redundant information, which makes HRV a more desirable parameter to BPBL estimation.

Limitations

There are several limitations in this study. The amounts of data used is not sufficient, more blood loss data are needed to increase the reliability of the BPBL estimation model. Future research should obtain more data to generate a more accurate BPBL model. Furthermore, a lot of parameters were extracted for this experiment, but a few of these parameters may only give a small contribution to the overall results, and more relevant parameters have not been identified. The relevance of other parameters to the BPBL needs to be verified, and more effective input parameters are to be used to improve the BPBL model.

Conclusions

In this article, we established three BPBL estimation models and compared their estimation results. The results of this study and the BPBL estimation model provide evidence that the RRI and HRV are good correlators with the BPBL and enhance the accuracy of the BPBL estimation. The comparison of the three models suggest that the HRV model, based on the characteristic parameters of HRV and PTT, has a better estimation of results during blood loss, thereby improving the accuracy of the BPBL estimation and therefore, being more suitable as a blood loss estimation model. This research on the process of blood loss and BP can be expanded to other fields, which will become one of its future directions. And it is hoped that this article will serve as a guidance for related research attempts in the future.

Abbreviations

BP: blood pressure; HRV: heart rate variability; PTT: pulse transit time; BPBL: blood pressure under blood loss; SBP: systolic blood pressure; MAP: mean arterial pressure; IBP: invasive blood pressure; RRI: R-R interval; PPG: photoplethysmography; PLS: partial least squares; Rt: correlation coefficient of the training set; Re: correlation coefficient of the estimation set; RMSEP: root means square error of the estimation set.

Declarations

224 **Ethics approval and consent to participate**

225 This study strictly followed the animal experiment guidelines and was approved by the Medical Ethics Committee of the
226 Chinese People's Liberation Army General Hospital (S2020-045-01).

227 **Consent for publication**

228 Not applicable.

229 **Availability of data and materials**

230 Due to the need for confidentiality, the datasets analyzed during the current study are not publicly available but are available
231 from the corresponding author on reasonable request.

232 **Competing interests**

233 The authors declare that they have no competing interests.

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238 **Authors' contributions**

239 GZ and HQW conceived and designed this study. ZGW and FXH wrote this article. JHW helps to check and revise articles. FC
240 and MY contributed to material support. All authors read and approved the final manuscript.

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242 Not applicable.

243 **Authors' information (optional)**

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Figure legend

Fig. 1. Basic theory of blood loss. On the left side of the picture, the blood in the blood vessel is composed of dynamic components and static components. The near-infrared light emitted by PPG passes through the bloodless tissue layer and blood of the human body and reflects back and is received by the sensor. Since the light intensity change curve of the reflected light is closely related to the pulse, PPG technology can be used to obtain the pulse wave waveform, and the AC and DC can be extracted from the pulse wave. In addition, AC is depending on the heart rate, so we calculated RRI to reflect blood changes together.

Fig. 2. Experimental scene diagram. The picture shows the side view of the pig on the operating table. During the experiment, we used the Chengdu Instrument RM6240C multi-physiological channel acquisition system to collect signals. We collected the PPG, ECG and IBP signals of the pig at the nose, chest and left femoral artery, respectively.

Fig. 3. Introduction to the experimental process. During the experiment, bloodletting and blood transfusion were performed when the physiological state of the pig was stable, and the specific number of times was determined by the physiological state of the pig. See text for further details.

Fig.4. The extraction of PTT, AC, and DC. (a) The PTT refers to the time that the pulse wave travels from the heart to the surrounding branch blood vessels during the pumping of the heart. (b) DC and AC refer to the peak value and amplitude of PPG respectively.

Fig. 5. Parameters for estimating BPBL. AC and DC are extracted from PPG, RRI and HRV are extracted from ECG, and PTT is calculated by ECG and PPG. These characteristic parameters are used to estimate the BPBL model.

Fig. 6. The results of the three blood loss models. The left side of the picture is the training set, and the right side is the prediction set. (a) The experimental results of PTT model. (b) The experimental results of RRI model. (c) The experimental results of HRV model.

Fig. 7. Bland-Altman plot of the difference between actual SBP and estimated SBP in three models. (a) the difference of PTT model. (b) the difference of RRI model. (c) the difference of HRV model.

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Table 1. Comparison of input parameters of three models.

BPBL Model	Input Parameters
PTT model	PTT, AC, DC, AC/DC
RRI model	PTT, AC, DC, AC/DC, RRI, PTT/RRI
HRV model	PTT, AC, DC, AC/DC, SDNN, RMSSD, HF

The input parameters of the PTT model are simply extracted by combining the ECG and PPG signals, and the input parameters of the RRI model and the HRV model are added with RRI and HRV based on PTT model, respectively.

Table 2. Comparison of experimental results of three models.

Blood Loss Model	Optimal Factor	Rt	RMSEC	Rp	RMSEP	P-value
PTT model	3	0.73	18.1 mmHg	0.77	16.8 mmHg	***
RRI model	5	0.89	12.2 mmHg	0.89	11.9 mmHg	***
HRV model	6	0.91	11.1 mmHg	0.92	10.6 mmHg	***

*** represents $P < 0.01$. Rt and Rp represent the Pearson correlation coefficients of the training set and prediction set, respectively. RMSEC and RMSEP represent the root mean square error of the training set and prediction set, respectively.

Figures

Figure 1

Basic theory of blood loss. On the left side of the picture, the blood in the blood vessel is composed of dynamic components and static components. The near-infrared light emitted by PPG passes through the bloodless tissue layer and blood of the human body and reflects back and is received by the sensor. Since the light intensity change curve of the reflected light is closely related to the pulse, PPG technology can be used to obtain the pulse wave waveform, and the AC and DC can be extracted from the pulse wave. In addition, AC is depending on the heart rate, so we calculated RRI to reflect blood changes together.

Figure 2

Experimental scene diagram. The picture shows the side view of the pig on the operating table. During the experiment, we used the Chengdu Instrument RM6240C multi-physiological channel acquisition system to collect signals. We collected the PPG, ECG and IBP signals of the pig at the nose, chest and left femoral artery, respectively.

Figure 3

Introduction to the experimental process. During the experiment, bloodletting and blood transfusion were performed when the physiological state of the pig was stable, and the specific number of times was determined by the physiological state of the pig. See text for further details.

Figure 4

The extraction of PTT, AC, and DC. (a) The PTT refers to the time that the pulse wave travels from the heart to the surrounding branch blood vessels during the pumping of the heart. (b) DC and AC refer to the peak value and amplitude of PPG respectively.

Figure 5

Parameters for estimating BPBL. AC and DC are extracted from PPG, RRI and HRV are extracted from ECG, and PTT is calculated by ECG and PPG. These characteristic parameters are used to estimate the BPBL model.

Figure 6

The results of the three blood loss models. The left side of the picture is the training set, and the right side is the prediction set. (a) The experimental results of PTT model. (b) The experimental results of RRI model. (c) The experimental results of HRV model.

Figure 7

Bland-Altman plot of the difference between actual SBP and estimated SBP in three models. (a) the difference of PTT model. (b) the difference of RRI model. (a) the difference of HRV model.