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Original citation & hyperlink:
Pan, F, He, P, Chen, F, Xu, Y, Zhao, Q, Sun, P & Zheng, D 2021, 'Evaluation of cuff deflation and inflation rates on a deep learning-based automatic blood pressure measurement method: a pilot evaluation study', Blood Pressure Monitoring, vol. 26, no. 2, pp. 129-134.
https://dx.doi.org/10.1097/MBP.0000000000000503

DOI 10.1097/MBP.0000000000000503
ISSN 1359-5237
ESSN 1473-5725

Publisher: Lippincott, Williams & Wilkins

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Evaluation of a deep learning based automatic blood pressure measurement method

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Conflicts of Interest and Source of Funding: This study was supported in partly by China Postdoctoral Science Foundation (Grant No. 2019M653409), in partly by Chengdu Science and Technology Bureau (Grant No. 2019-YF05-00109-SN), in partly by Sichuan Science and Technology Program (Grant No. 2020YJ0282) and in partly by the National Natural Science Foundation of China (Grant No. 61701050). The experiment was conducted with the support from the Engineering and Physical Sciences Research Council (EPSRC) Healthcare Partnership Award (Grant No. EP/I027270/1). There is no conflict of interest.

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Abstract

Objective: The aim of this study was to evaluate the performance of using a deep learning-based method for measuring systolic and diastolic BPs (SBPs and DBPs) and the effects of cuff inflation and deflation rates on the deep learning-based BP measurement (in comparison with the manual auscultatory method).

Methods: Forty healthy subjects were recruited. SBP and DBP were measured under four conditions (i.e., standard deflation, fast deflation, slow inflation and fast inflation) using both our newly developed deep learning-based method and the reference manual auscultatory method. The BPs measured under each condition were compared between the two methods. The performance of using the deep learning-based method to measure BP changes was also evaluated.

Results: There were no significant BP differences between the two methods ($P > 0.05$), except for the DBPs measured during the slow and fast inflation conditions. By applying the deep learning-based method, SBPs measured from fast deflation, slow inflation and fast inflation decreased significantly by 3.0, 3.5 and 4.7 mmHg (all $P < 0.05$), respectively, in comparison with the standard deflation condition. Whereas, corresponding DBPs measured from the slow and fast inflation conditions increased significantly by 5.0 and 6.8 mmHg, respectively (both $P < 0.05$). There were no significant differences in BP changes measured by the two methods in most cases (all $P > 0.05$, except for DBP change in the slow and fast inflation conditions).

Conclusion: This study demonstrated that the deep learning-based method can achieve accurate BP measurement under the deflation and inflation conditions with different rates.

Keywords: Blood pressure measurement, deep learning, cuff inflation, cuff deflation

Introduction

The importance of accurate and reliable blood pressure (BP) measurement is without doubt.[1] The most common method for non-invasive BP measurement (manual auscultatory and automated oscillometric methods) is to use a cuff, which can be inflated and deflated to provide BP readings. Several international bodies including the American Heart Association (AHA), the British Hypertension Society (BHS) and the European Society of Hypertension (ESH), recommend that BP should be measured during cuff deflation with the rate of 2-3 mmHg per second.[2-6] However, in order to reduce the time of measurement and pressure required, some automatic oscillometric devices measure BPs during cuff inflation.[7, 8]

Some researchers quantified the influence of different cuff deflation and inflation rates on BP measurement. King compared the auscultatory BPs measured by two deflation rates of 2.35 and 4.7 mmHg per second, and found a significant effect.[9] Zheng et al. reported the effect of cuff pressure deflation rate on both manual auscultatory and automatic oscillometric BP measurements, indicating that, by using manual technique, accurate BP measurement could be achieved only if the deflation rate is slow as recommended, whereas the deflation rate had little effect on the measurement by using automatic model-based oscillometric techniques.[10] Our previous publication also compared BPs obtained from healthy volunteers during inflation with those during deflation, and found significant differences with those measured during cuff inflation.[11]

With increasing use of automatic BP devices by the general public as well as many healthcare institutions, the inability of highly accurate BP measurement by oscillometric technique has been reported by researchers.[12, 13] Recently, deep learning techniques have been applied to medical fields with impressive outcomes.[14-16] Deep learning techniques have multiple layers of nonlinear processing and can automatically detect and analysis complex, high-level features from raw data sources. We have developed a new BP measurement method, to identify Korotkoff sound (KorS) by using a deep learning technique. Its performance has been assessed under non-resting conditions (deeper breathing, talking and arm movement) during standard cuff deflation.[17, 18] However, there is no comprehensive investigation of the effect on our proposed method regarding the fast cuff pressure deflation rate and cuff pressure inflation rate. As a newly developed deep learning-based BP measurement method, it is clinically important to evaluate its performance under different measurement conditions.

The aim of this study is to provide quantitative evidence of the effect on the deep learning-based BP measurement in terms of different cuff deflation and inflation rates[17], and evaluate its performance of measuring BP changes under different cuff deflation and inflation rates in comparison with the manual auscultatory method.

Methods

Subjects

International Standards Organization (ISO) requires that the overall mean and standard deviation (SD) of the difference between a new BP measurement technique and the reference BP (from manual auscultatory method) should be within 5 and 8 mmHg, respectively.[19] Sample size calculation was performed based on a paired t-test for mean difference to allow a mean 5 mmHg BP difference to be detected with a typical 8 mmHg SD of BP measurement. 21 subjects were therefore enough to achieve a confidence level of 95% and a statistical power of 80%. A total of 40 normotensive subjects (30 male and 10 female) were enrolled in this study. Mean age was 43 ± 12 ranging from 23 to 65 years, mean height was 173 ± 10 cm, mean weight was 73 ± 11 kg, and mean arm circumference was 28 ± 2.7 cm. The experiment was carried out according to the Declaration of Helsinki of the World Medical Association, and received ethical permission from the Newcastle & North Tyneside Research Ethics Committee. All participants provided their written informed consent to participate in the study.

Manual auscultatory blood pressure measurement

As shown in Figure 1(a), manual auscultatory SBP and DBP were measured with a sphygmomanometer and stethoscope by a trained operator in a quiet and temperature-controlled clinical measurement room. Before the measurement, the subject was asked to rest on a chair for 10 mins. The entire procedure followed the recommendations of the European and British Hypertension Societies.[20]

There were three repeated sessions for each subject, and an automatic and programmable air pump was used to control the cuff deflation or inflation rate. Within each session, four conditions were considered, each of which has a different cuff deflation or inflation rate (one measurement for each condition): standard linear deflation at 2-3 mmHg/s, fast linear deflation at 5-6 mmHg/s, standard linear inflation at 2-3 mmHg/s, and fast linear inflation at 5-6 mmHg/s. The order of each measurement was randomized within each session. Subjects were allowed to rest for at least 4 mins between sessions and 1 min between measurements. Totally, twelve measurements were performed for each subject.

The following manual BP measurement principle was followed. During cuff deflation, manual SBP and DBP were determined at the appearance and disappearance of the Korotkoff sounds, while during cuff inflation, manual SBP and DBP were determined at the disappearance and appearance of the Korotkoff sounds. The BP measured under standard cuff deflation condition was considered as the reference BP for each subject.

Deep learning-based blood pressure measurement

During twelve manual measurements for each subject, as demonstrated in Figure 1(a), the KorS and cuff pressure signals were recorded synchronously to a data capture computer via a Y-tube at a sampling rate of 2000 Hz. The highest frequency of KorS signal has been reported as about 400 Hz;[21] thus, our sampling rate is 5 times of this highest frequency. According to the Nyquist Sampling Theorem (the sampling rate must be at least 2 times the highest frequency of the signal to be recorded), the key information of the KorS signal is kept with the sampling rate of 2000 Hz. Figure 1(b) gives typical examples of the recorded KorS and cuff pressure corresponding to two rates of deflation and inflation. These digitally saved data were used for subsequent offline BP determination by our recently developed deep learning-based method.[17] Briefly, the recorded KorS was firstly segmented into beat-by-beat frames (1s window with 2000 sample points per frame) centered within the oscillometric pulse (extracted from the record cuff pressure). Secondly, each frame was converted into matrix 'images' by short time Fourier transformation (STFT), and then sent to a trained convolutional neural network (CNN) to identify the audible KorS and non-audible KorS beats. Lastly, the SBP and DBP were respectively determined by the cuff pressure corresponding to 1) the first and last audible KorS beats during deflation; and 2) the last and first audible KorS beats during inflation.

The whole process was performed using a computer with Windows Operating System with CPU (AMD Ryzen 5 2600 @ 3.4 GHz) and GPU (NVIDIA GTX 1080). The processing time mainly includes the time for preprocessing, neural network prediction and BP matching. Depending on the slow or fast inflation, the processing time was about 0.4 and 0.2 s, which was negligible. The processing time difference was caused by different number of beats used for processing during the period of inflation. The inflation time was calculated based on the inflation speed. For example, with the slow inflation speed of 2-3 mmHg/s, in order for the cuff pressure to be inflated from 20 mmHg to 200 mmHg, the time required is 66.7 s.

Data and statistical analysis

SPSS software package (SPSS Inc., Chicago, IL, USA) was used to analyze the measurement repeatability from each condition of the two methods. The value of $P < 0.05$ was considered as statistically significant difference. The manual auscultatory method is regarded as the gold standard of non-invasive BP measurement; thus it has been widely accepted and used as reference measurement. In order to investigate the measurement accuracy of our deep learning-based method, the mean and SD of BP differences between the deep learning-based method and the manual auscultatory methods (reference) were calculated separately for the four measurement conditions (standard deflation, fast deflation, standard inflation and fast inflation).

Next, in order to investigate BP changes caused by different measurement conditions (inflation and deflation, and their rates), the mean and SD of BP differences between the measurements taken during standard deflation and each of the other three conditions were calculated respectively for both the manual and deep learning-based methods, and then compared between the two methods.

Analysis of variance (ANOVA) with post-hoc multiple comparisons were applied to investigate the effects of cuff inflation and deflation rates on measuring BPs and the significant difference between the BPs taken during standard deflation and those obtained during each of other three conditions.

Results

Repeatability between measurements

Statistical analysis showed that, for both the deep learning-based and manual auscultatory methods, there was no significant BP difference (for both SBP and DBP) between the repeat sessions (all $P > 0.05$). This indicated that in neither method were the measurements influenced by the previous session or by the sequential order. The means from the three repeats for each subject was then used for the following analysis.

BP differences between the two methods

The overall mean and SD of BP differences between the two methods are shown in Table 1, respectively for each of the four conditions. In comparison with the manual auscultatory method, DBP determined by the deep learning-based method was significantly higher by 2.56 mmHg and 1.99 mmHg, respectively, from in slow and fast inflation cycles (both $P < 0.05$). Otherwise, there was no significant BP differences between two methods (all $P > 0.05$). A detailed distribution of these differences is shown in Table 2, which shows the percentage of these differences falling within 5, 10, and 15 mmHg. It can be observed that, the performance of the deep learning-based method is within the Grade A standard for BP device by BHS (i.e., 60%, 85% and 95% of SBP and DBP differences are within 5, 10 and 15 mmHg, respectively) under each of the four measurement conditions.

Effect of cuff deflation and inflation rates on measured BP

The mean paired differences between each of the three measurement conditions (i.e., fast deflation, slow inflation and fast inflation) and the standard deflation condition are given in Table 3, respectively for the two methods. The key finding is that, for the deep learning-based method, the mean SBPs measured from fast deflation, slow inflation and fast inflation decreased significantly by 3.0, 3.5 and 4.7 mmHg, respectively, in comparison with those obtained in the standard deflation condition (all $P < 0.05$). Whereas, the mean DBPs measured in slow inflation and fast inflation increased significantly by 5.0 and 6.8 mmHg, respectively, when compared with standard deflation condition (both $P < 0.05$). It also can be observed that, DBP of fast deflation increased significantly by 0.9 mmHg ($P = 0.03$) using the manual method, while there was no significant difference from the deep learning-based method. Additionally, the BP differences were caused by different measurement conditions in reference to standard deflation condition. They were not measurement errors.

Comparison of BP changes between the two methods

As shown in Figure 2, there were no significant differences in BP changes measured by the deep learning-based and manual methods (all $P > 0.05$, except DBP measured during slow and fast inflation). This indicated that the small BP changes caused by different cuff inflation or deflation rates can be accurately measured by the deep learning-based method.

Discussion

The present study has quantitatively evaluated the effects of cuff inflation and deflation rates on BP measurements using the deep learning-based and manual auscultatory methods. In this study, the deep learning-based method achieved less than 1 mmHg measurement error (all SD < 4 mmHg) from the majority of measurement conditions (except the DBP from slow and fast cuff inflation). This level of accuracy was within the requirement of BP device validation from the BHS. This finding emphasized that the deep learning-based method could achieve accurate measurement under both deflation and inflation conditions with different rates.

The DBPs measured by the deep learning-based method have not achieved statistically non-significant difference from slow and fast cuff inflation in comparison with manual method (with 2.56 and 1.99 mmHg statistically significantly higher DBP respectively from slow and fast cuff inflation, both $P < 0.05$). Figure 3 demonstrates an example of DBP identification difference by two methods during cuff inflation. It is within the Grade A standard for BP device by BHS (see Table 2). One possible explanation for the DBP error can be caused by the small amplitude and weak audible characteristics of KorS in the DBP region, as shown in Figure 1(b). This leads to inaccurate identification of KorS in the DBP region by our deep learning-based method. In future studies, additional pre-processing algorithms may be required to enhance the small amplitude and weak audible KorS.

Another finding is that, the cuff inflation and deflation rates had significant influence on measured BPs. With the BP measurement performed during cuff inflation, the deep learning-based SBPs were significantly lower than those obtained during standard cuff deflation, whereas deep learning-based DBPs were significantly higher. These results are consistent with our previous study with automated oscillometric method.[11] One possible explanation is due to the different mechanical behavior of the brachial artery during cuff inflation and deflation. Vychytil et al. reported different arterial mechanical response from the inflation-deflation cycle test on animal arteries.[22] The transmural pressure of artery is the difference between internal blood pressure and external cuff pressure. It changes from positive to negative during cuff inflation, and from negative to positive during cuff deflation. During cuff deflation, with the external pressure above SBP, it is likely that the brachial artery above the cuff will be fully expanded, which is caused by the cardiac pressure without blood flow. During cuff inflation, the arterial pressure could be slightly lower because there is some flow for each cardiac beat preceding the SBP. Hence, the external pressure needed to collapse and open the artery during inflation and deflation, respectively. Both Zheng et al.'s and Fabian et al.'s groups have found the difference in mean arterial pressure (MAP) measured by oscillometric BP technique during cuff inflation and deflation, indicating that the response and the maximum compliance of the artery are different between cuff inflation and deflation, because the artery has the maximum compliance when external pressure is equal to the arterial MAP.[11, 23] SBPs measured from fast cuff deflation were lower than that from standard cuff deflation, which is in agreement with Zheng's report.[10] Therefore, the effect of cuff inflation and deflation rates on BP is expected to be similar with the manual auscultatory method or the oscillometric method. More importantly, this study has demonstrated that there was no significant difference in BP changes (i.e., the difference between the standard cuff deflation condition and each of the three conditions) determined by the manual and deep learning-based methods (except DBP measured during cuff inflation). Hence, one key finding of our study is that the small BP changes caused by different measurement condition can be accurately measured by the deep learning-based method in reference to the manual auscultatory method, and our proposed deep learning-based method is an effective technique for measuring small BP changes.

One limitation of this study is that, although 40 subjects used in this study were sufficient for a study focusing on technology development and comparison, the total sample size and population was too small for a clinical population study or a proper clinical validation study. A future study with larger sample size including hypertensive and hypotensive participants is needed to investigate whether similar results could be achieved. It would also be interesting to explore and quantify the differences of amplitude and frequency of KorS between cuff deflation and inflation.

Another limitation is that, a better comparison would have been to use the true invasive reference measurement; however, the manual auscultatory method is regarded as gold standard of non-invasive BP measurement, and used for automatic BP device validation. As shown in Table 1, differences in BP readings between the two methods were less than 0.5 mmHg under most of the measurement conditions, which is acceptable for automatic BP device validation stage. Furthermore, it is worth comparing the performance of our method with the commonly used automatic BP devices based on oscillometric technique. Nevertheless, this pilot study evaluated our newly developed deep learning-based method by analyzing the stethoscope and cuff pressure signals from a physiological recording system. The results demonstrated that our deep learning-based method can be developed further to achieve enough accuracy from the manual auscultatory method.

In summary, this study provides quantitative evidence that our newly developed deep learning-based BP measurement method can achieve accurate measurement under different deflation and inflation rates.

Acknowledgements

This study was supported in partly by China Postdoctoral Science Foundation (Grant No. 2019M653409), in partly by Chengdu Science and Technology Bureau (Grant No. 2019-YF05-00109-SN), in partly by Sichuan Science and Technology Program (Grant No. 2020YJ0282) and in partly by the National Natural Science Foundation of China (Grant No. 61701050). The experiment was conducted with the support from the Engineering and Physical Sciences Research Council (EPSRC) Healthcare Partnership Award (Grant No. EP/I027270/1).

There is no conflict of interest.

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Captions

Figure 1. (a) Demonstration of manual auscultatory blood pressure measurement and the measurement system for Korotkoff sound and cuff pressure recording. (b) Examples of recorded cuff pressure and Korotkoff sound waveform from four measurement conditions (standard cuff deflation, fast cuff deflation, slow cuff inflation and fast cuff inflation).

Figure 2. Comparison of BP changes (mean ± s.e.m.) measured by the deep learning based and manual methods. * Significant difference between comparisons ($P < 0.05$).

Figure 3. An example of DBP determination difference between the deep learning based method and manual auscultatory method during cuff inflation.

Table 1. Overall mean differences ± SD of BP between deep learning method and manual auscultatory method under different measurement conditions.

Condition	*Mean differences of BPs between deep learning and manual method*	
	SBP (mmHg)	DBP (mmHg)
Standard Deflation	-0.22 ± 1.23	0.48 ± 2.29
Fast Deflation	-0.50 ± 1.97	-0.15 ± 1.66
Slow Inflation	0.20 ± 3.77	2.56 ± 2.26*
Fast Inflation	0.57 ± 2.87	1.99 ± 3.11*

* Significantly different ($P < 0.05$)

Table 2

Table 2. Distribution of BP differences between the deep learning method and manual auscultatory method under different measurement conditions.

Condition		Within 5 mmHg (%)	Within 10 mmHg (%)	Within 15 mmHg (%)
Standard Deflation	SBP	96.6	100	100
	DBP	89.7	98.3	100
Fast Deflation	SBP	87.7	100	100
	DBP	93.0	99.1	100
Slow Inflation	SBP	78.6	90.6	97.4
	DBP	77.8	96.6	99.2
Fast Inflation	SBP	83.3	95.6	98.3
	DBP	70.2	95.6	100

Table 3. Overall mean differences ± s.e.m. of BP when compared with the value for standard deflation condition

Measurement condition	*Mean differences of BP referenced to the cuff standard deflation condition (mmHg)*			
	Deep learning Method		*Manual auscultatory method*	
	SBP	DBP	SBP	DBP
Fast Deflation	-3.0 ± 0.5*	0.2 ± 0.5	-2.8 ± 0.4*	0.9 ± 0.5*
Slow Inflation	-3.5 ± 0.9*	5.0 ± 0.5*	-3.9 ± 0.7*	2.9 ± 0.5*
Fast Inflation	-4.7 ± 0.9*	6.8 ± 0.6*	-5.6 ± 0.8*	5.3 ± 0.6*

* Significantly different ($P < 0.05$) in comparison with the cuff standard deflation condition.

Figure 1

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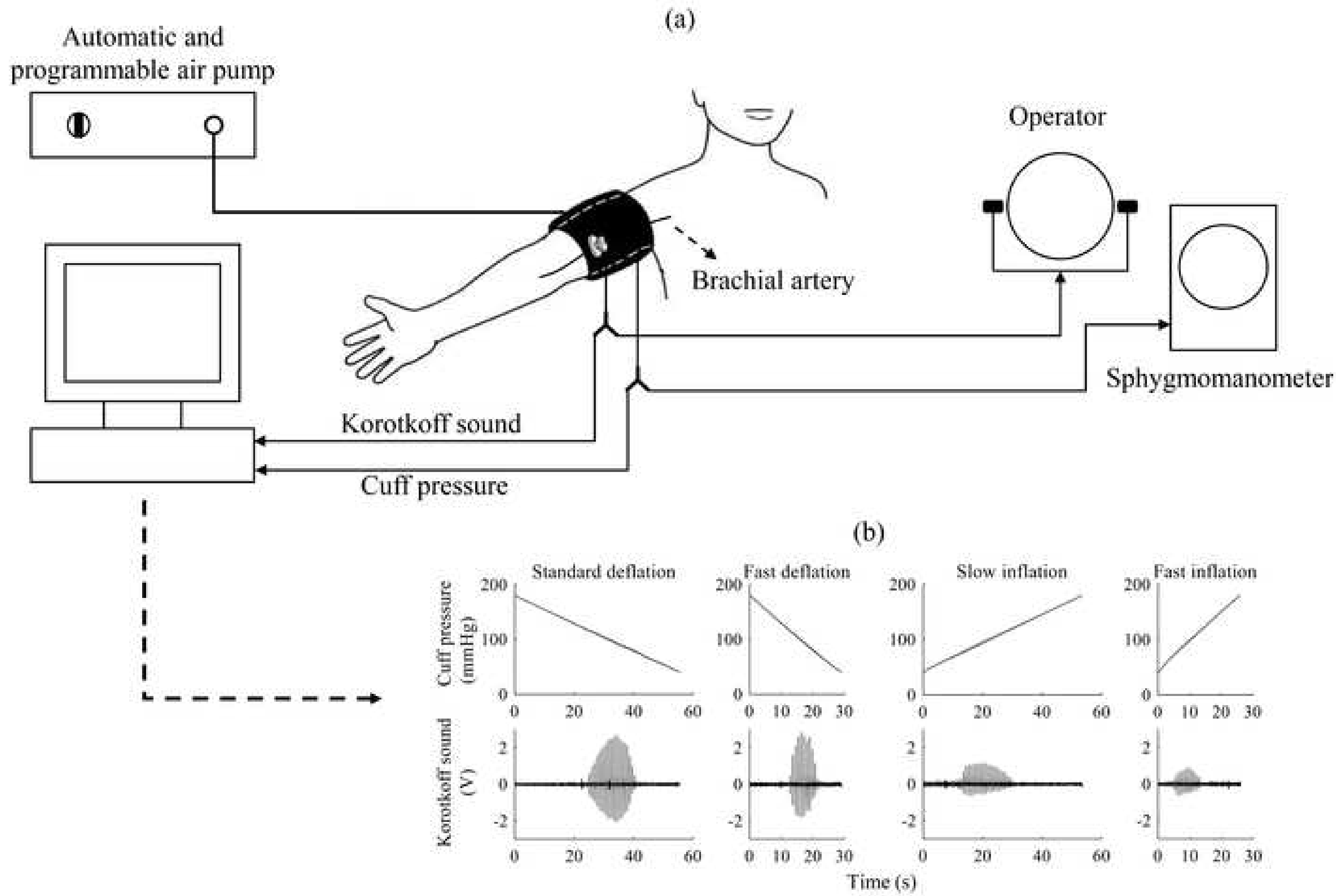

Figure 2

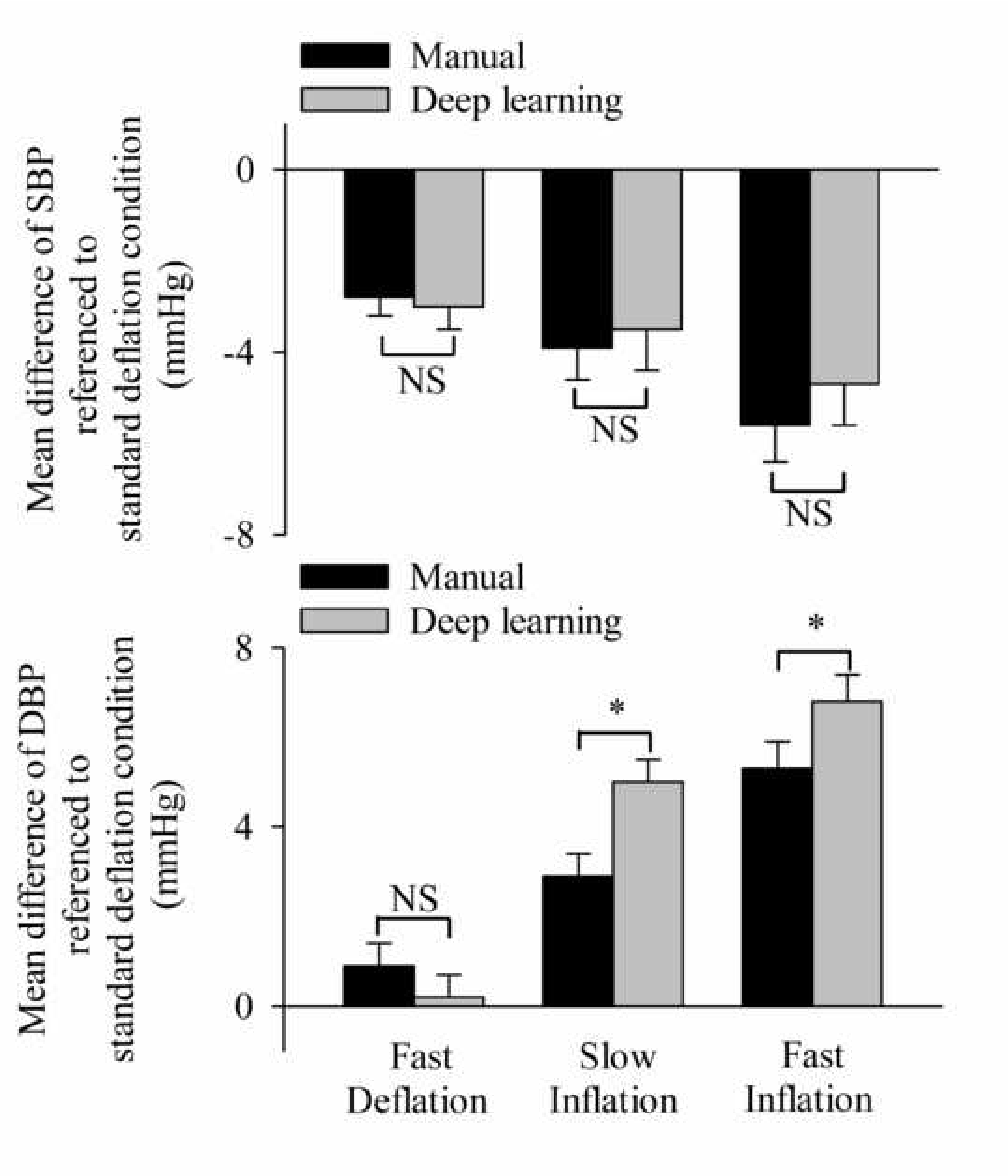
Manual
Deep learning
Mean difference of SBP referenced to standard deflation condition (mmHg)
0
-4
-8
NS
NS
NS
Manual
Deep learning
Mean difference of DBP referenced to standard deflation condition (mmHg)
8
4
0
NS
*
*
Fast Deflation
Slow Inflation
Fast Inflation

Figure 3 Click here to access/download;Figure;Figure 3.tif