Increasing the sensor channels: a solution for the pressing offsets that cause the physiological parameter inaccuracy in radial artery pulse signal acquisition

Chao Chen[1], Zhendong Chen[1], Hongmiin Luo[2], Bo Peng[3,4]*, Yinan Hao[3], Xiaohua Xie[1]*, Haiqing Xie[5] and Xinxin Li[6]

[1]School of Computer Science and Engineering, Sun Yat-Sen University, Guangzhou, China, [2]Science and Technology Innovation Center, Guangzhou University of Chinese Medicine, Guangzhou, China, [3]Department of Musical Instrument Engineering, Xinghai Conservatory of Music, Guangzhou, China, [4]Sniow Research and Development Laboratory, Foshan, China, [5]School of Medical Engineering, Foshan University, Foshan, China, [6]School of Nursing, Sun Yat-Sen University, Guangzhou, China

Introduction: In studies of pulse wave analysis, single-channel sensors only adopt single temporal pulse signals without spatial information to show pulse-feeling patterns. Multi-channel arterial pulse signals, also named as three-dimensional pulse images (3DPIs), provide the spatial and temporal characteristics of radial pulse signals. When involving single or few-channel sensors, pressing offsets have substantial impacts on obtaining inaccurate physiological parameters like tidal peak (P_2).

Methods: This study discovers the pressing offsets in multi-channel pulse signals and analyzes the relationship between the pressing offsets and time of P2 (T_2) by qualifying the pressing offsets. First, we employ a data acquisition system to capture 3DPIs. Subsequently, the errorT_2 is developed to qualify the pressing offsets.

Results: The outcomes display a central low and peripheral high pattern. Additionally, the errorT_2 increase as the distances from the artery increase, particularly at the radial ends of the blood flow direction. For every 1 mm increase in distances between sensing elements and center sensing elements, the errorT_2 in the radial direction escalates by 4.87%. When the distance is greater than 3.42 mm, the errorT_2 experiences a sudden increase.

Discussion: The results show that increasing the sensor channels can overcome the pressing offsets in radial pulse signal acquisition.

1 Introduction

Cardiovascular diseases (CVD) are the primary causes of death globally (Visseren et al., 2021). Pulse waves are generated by cardiac ejection during heart cycles and play a significant role in cardiovascular health. Pulse wave analysis (PWA), considered an essential diagnostic tool for assessing cardiovascular disease, detects early pathological modifications, such as arterial stiffness and endothelial dysfunction (AlGhatrif et al., 2013; Matsuzawa et al., 2015; Francque et al., 2016; Ohkuma et al., 2017; Chen et al., 2021). The roles of PWA in the diagnosis of CVDs

FIGURE 1
3DPIs during a cardiac cycle: **(A)** One-dimensional radial arterial pulse wave and four key physiological points; **(B)** Stereoscopic (upper left side) and planar (upper right side) 3DPIs at the T_2 with normalized sensing length, width, and pulse amplitude; data acquisition by a sensor from a radial artery (lower side).
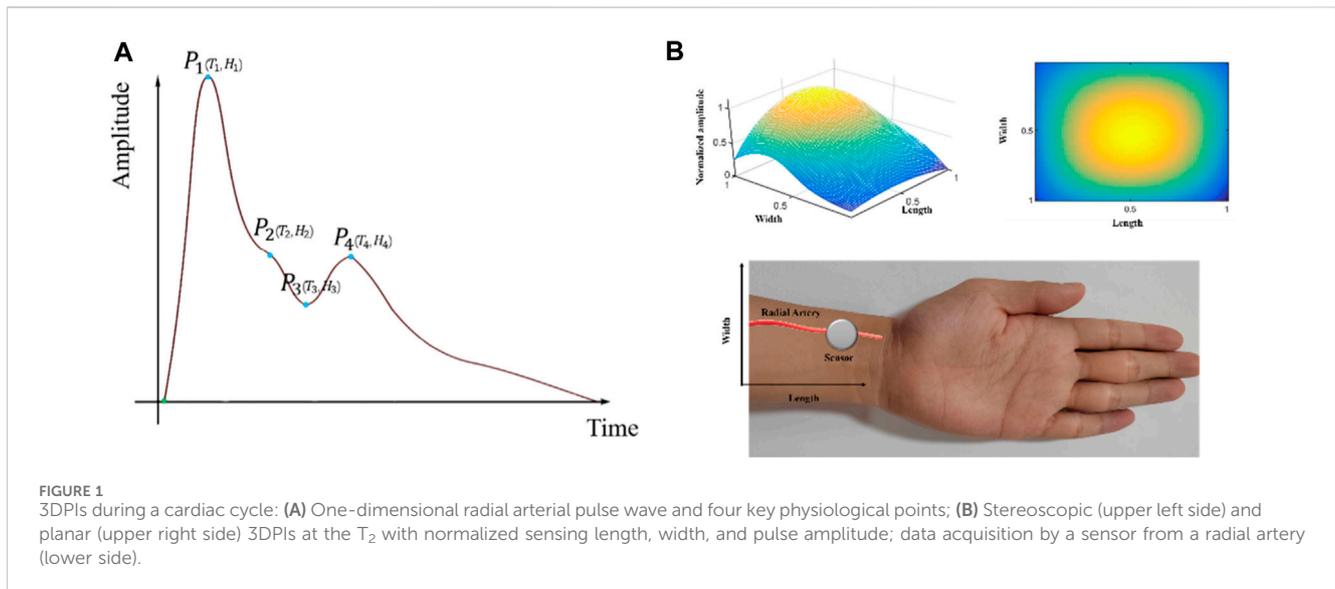
encompass the assessment of arterial stiffness, pulse wave velocity analysis, and pulse waveform analysis. Several physiological parameters, such as the peripheral augmentation index (pAIx), pulse transit time (PTT), reflection magnitude (RM), and reflection index (RI), are employed in PWA (Munir et al., 2008; Wang et al., 2010; Milicevic et al., 2020; Yao et al., 2022; Campitelli et al., 2023). The tidal peak (P_2), representing the second wave peak of the pure radial arterial pulse signals within a cardiac cycle, is one of the four key physiological points, which also include percussion peaks (P_1), diastolic notches (P_3), and diastolic peaks (P_4) (Su et al., 2016). These points represent key temporal markers within each cardiac cycle, conveying essential information about cardiovascular health. The P_2 reflects the pressure wave originating from peripheral resistance vessels, which reflects the amplitudes of arterial stiffness and is crucial in the assessment of arterial stiffness (Peng et al., 2022; Chen et al., 2023). Figure 1A illustrates the positions of the four key physiological points during a cardiac cycle.

To measure radial pulse signals, a series of acquisition devices have been developed and applied in pulse acquisition (Luo et al., 2012a; Qiao et al., 2018; Tsai et al., 2018; Fu et al., 2019; Huang et al., 2019). These devices employ sensors with one sensing element to capture radial pulse signals. However, these single-channel sensors only adopt single temporal pulse signals without spatial information to show pulse-feeling patterns (Kim et al., 2011; Kim et al., 2012; Huang et al., 2019). In recent years, multi-channel pulse signals have been widely measured using tactile sensors for pulse signal application studies (Chung et al., 2011; Kong et al., 2016; Peng et al., 2019; Zhang et al., 2021; Liu et al., 2023). The multi-channel arterial pulse signals, also named as three-dimensional pulse images (3DPIs), provide the three-dimensional spatial and temporal characteristics of pulse signals (Peng et al., 2019). 3DPIs also enhances the visualization of pulse signals and provides more cardiovascular-related information. During data acquisition, 3DPIs at T_2 (time of P_2) are often focal points of interest (Cui et al., 2019; Yuen et al., 2019; Luo et al., 2021). Figure 1B displays the stereoscopic/planar 3DPIs at the T_2 and data acquisition by a sensor from a radial artery. Most devices for obtaining 3DPIs fix the tactile sensors, which are a kind of multi-channel sensors, on the robotic finger and control the robotic finger to press on the position of radial arteries to

acquire the pulse signals (Chung et al., 2011; Si et al., 2011; YF et al., 2011; Luo et al., 2012a; Luo et al., 2012b; Chung et al., 2012; Hu et al., 2012; Chung et al., 2013; Luo and Chung, 2016; Luo et al., 2016; Luo et al., 2018; Peng et al., 2019).

During the pressing process, the T_2 are different in all channels of the tactile sensors (Peng et al., 2019). However, in scenarios involving sensors with one or few sensing elements, pressing offsets are inevitable. In such cases, the operators may face difficulties in judging whether the pressing process is accompanied by offsets since the sensitivities of single-channel sensors are not uniform (Dario and Bergamasco, 1988; Dario and Buttazzo, 2016; Fearing, 2016). Subsequently, operators may encounter challenges in obtaining multi-channel pulse signals that reflect true arterial conditions. Then, operators may obtain inaccurate physiological parameters like T_2. Operators encounter a challenge when detecting pressing offsets during the acquisition of multi-channel pulse signals due to the lack of appropriate quantitative tools for this purpose. By detecting whether any offsets occur during the pressing process, operators can adjust the pressing position to ensure the acquisition of 3DPIs that accurately reflect the arterial conditions.

This study discovers the pressing offsets in multi-channel pulse signals and analyzes the relationship between the pressing offsets and T_2 by qualifying the pressing offsets in pulse signal acquisition. First, we employ a data acquisition system to capture 3DPIs from the subjects. Then, the errors between each channel and the best channel in 3DPIs are determined to qualify the pressing offsets in the tactile sensor. Finally, the subjects are divided into multiple control groups, and the results are compared and analyzed. Due to the high sensitivity and mature fabric technologies, operators prefer to employ tactile sensors to obtain pulse signals (Yang et al., 2017). In this study, we employ the tactile sensors developed by PPS (Pressure Profile Systems Inc., Los Angeles, CA, United States), which are widely recognized as the preferred choice for acquiring physiological signals across a diverse range of clinical environments (Cui et al., 2019). PPS tactile sensors are designed with exceptional sensitivity and accuracy to detect tiny changes in pressure that are indicative of pulse signals. Electrodes as sensing elements are arranged in orthogonal, overlapping strips to create a tactile sensor. The electrodes overlap at each position to form a
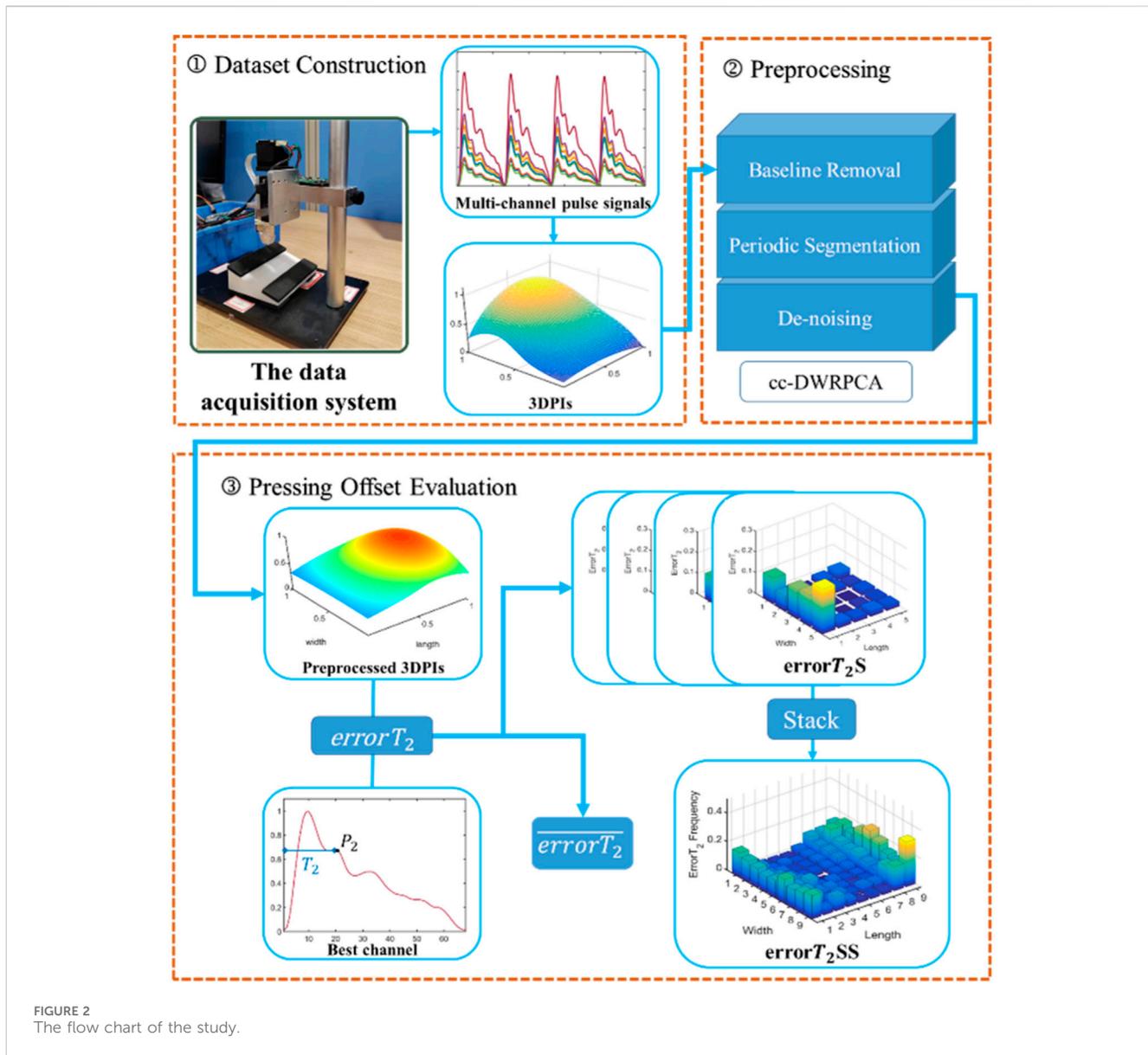
FIGURE 2
The flow chart of the study.

TABLE 1 Subject characteristics in this study (Mean ± Standard Deviation).

	All	Male	Female
Number	52	44	8
Age (year)	59.98 ± 14.94	59.64 ± 15.47	61.88 ± 15.47
Height (cm)	164.25 ± 7.48	165.59 ± 6.673	156.88 ± 6.67
Weight (kg)	72.17 ± 12.91	72.45 ± 12.97	70.63 ± 12.97
BMI (kg/m^2)	26.68 ± 4.00	26.32 ± 3.77	28.67 ± 3.77
Systolic BP (mmHg)	136.96 ± 23.59	135.70 ± 21.25	143.88 ± 21.25
Diastolic BP(mmHg)	80.17 ± 14.03	81.20 ± 13.70	74.50 ± 13.70
Heart rate (beats/min)	69.54 ± 10.30	70.39 ± 9.12	64.88 ± 9.12

discrete capacitor. A single row and column are selectively scanned to determine the capacitance and pressure (Hu et al., 2012). PPS sensors offer the ability to customize tactile sensors to meet specific research or clinical needs, thus PPS sensors come in a variety of specifications. In this article, a PPS sensor with 5 rows and 5 columns is denoted as a 5 × 5 sensor. The 5 × 5–1 PPS sensor can provide a tactile center point by positioning the blank area in the corner (Peng et al., 2019).

The rest of this paper is organized as follows. In Methods section, data construction, preprocessing, and pressing offset evaluation are introduced. The Results section illustrates the results of different control groups. Lastly, the final section concludes with a discussion of the experimental results.

2 Materials and methods

Figure 2 presents a comprehensive depiction of the entire workflow, consisting of three primary stages: dataset construction, preprocessing, and pressing offset evaluation. The dataset construction section involves utilizing a multi-channel pulse acquisition device to capture pulse signals from the subjects. Subsequently, the acquired pulse wave dataset

FIGURE 3
The data acquisition system in this study.
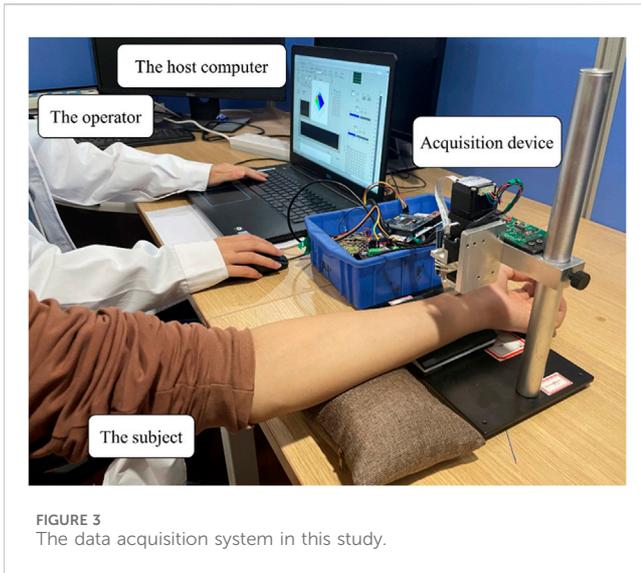
employ two strategies to ensure the accurate acquisition of 3DPIs. We utilize a specialized pulse signal acquisition device, which include PPS sensors, the most popular tactile sensors, and follow stringent data collection protocols. A PPS sensor, a fixture, a robotic finger, a stepper motor (to control the pressing depth of the robotic finger), and a main control board make up the uniaxial device (Figure 3). This study utilizes a PPS tactile sensor with an 85 Hz sampling rate. The rectangular geometry of a sensing element in the PPS tactile sensor is 1.25×1.71 mm (Peng et al., 2019). The main control board, based on STM32 (Jin et al., 2019), is responsible for managing the underlying hardware, collecting PPS data, and establishing serial port communication with the host computer. Pulse signals are detected using a 24-channel PPS tactile sensor. Subjects are scheduled to sit in a chair in a quiet room for a minimum of 10 min before their pulse signals are recorded. The operator can easily handle the computer and oversee the measurement process while the subject is comfortably tested on their wrist at the same height as their heart due to their proper relative locations. The data collection process adheres strictly to the protocol established in our previous research (Peng et al., 2019).

undergoes preprocessing, which includes baseline removal, periodic segmentation, and de-noising. Finally, the preprocessed data is then utilized for calculating the $\overline{errorT_2}$ and facilitating the construction of errorT$_2$SS.

2.1 Dataset construction

2.1.1 Data acquisition

This study employs a data acquisition system for capturing pulse signals from subjects. In the data acquisition system of this study, we

2.1.2 Subjects and control groups

The institutional review board at the National Cheng Kung University Hospital granted authority for this study to conduct a human trial (Approval Number: B-ER-103-263). The collected personal data from 52 subjects, with sequentially acquired valid data for both hands, is examined and analyzed (Table 1). Among the subjects, 15 are non-hypertensive subjects, and 37 are hypertensive patients. Finally, 623 multicycle pulse signal samples with 24 channels ($5 \times 5-1$) are acquired. In this study, the subjects are divided into three control groups: left hands/right hands, male/female, and non-hypertensive/hypertensive.

FIGURE 4
The stacking process of the errorT$_2$SS.

FIGURE 5
The errors between each channel and the best channel of all subjects: **(A)** The heat map of the errorT$_2$SS for all subjects, with deeper colors indicating higher frequencies and larger error values; **(B)** The 3D bar chart of the errorT$_2$SS for all subjects, where the z-axis represents the errorT$_2$ values; **(C)** The radial weighted errorT$_2$−distance boxplot of all subjects, x-axis represents the distance between sensing elements and center sensing elements, y-axis represents the radial weighted errorT$_2$, a unit of the x-axis represents 1.71 mm; **(D)** The axial weighted errorT$_2$−distance boxplot of all subjects, a unit of the x-axis represents 1.25 mm. A sensing element is a channel in a sensor. The red arrow indicates the direction of blood flow.

2.2 Preprocessing

Numerous studies have employed a thorough and suggested pulse signal pipeline to preprocess pulse signals (Wang et al., 2016; Peng et al., 2019; Peng et al., 2022; Song et al., 2023). In this section, a complete preprocessing pipeline includes baseline removal, periodic segmentation, and de-noising.

First, to eliminate baseline wandering from the signals, a first-order Butterworth high-pass filter with a cut-off frequency of 0.5 Hz is applied (Li, 2007). Second, the multi-channel signals are segmented into individual single-period pulse signals for the de-noising demand of the subsequent algorithm. Finally, a de-noising algorithm called Cross-Channel Dynamic Weighting Principal Component Analysis (cc-DWRPCA) is implemented to de-noise the processed pulse signals (Peng et al., 2022).

The cc-DWRPCA, based on Robust Principal Component Analysis (RPCA) (Candès et al., 2011), employs a channel-scaled factor (CSF) technique to manipulate the weights ω among channels (see Eq. 1), which can get superior performances than weighted robust principal component analysis (WRPCA) (He et al., 2019). Without using the inherent correlations between these channels, WRPCA is able to extract signal properties for each channel

independently. After de-noising with cc-DWRPCA, 623 single-cycle pulse signals with 5 × 5–1 are extracted.

$$\omega_C = \frac{\eta}{\sigma_C(D) + \varepsilon}, \tag{1}$$

where ω_C is the weight of the cth channel of a subject, η denotes the cth CSF of D in the c-th channel, $\sigma_C(D)$ represents cth singular value of D, D is the singular value decomposition of a multicycle pulse signal, ε is the reconstruction error tolerance, which is set to 1e-6 in this study.

To obtain a complete 5 × 5 matrix, we employed interpolation to generate an additional channel for each sample, transforming the 5 × 5–1 matrix (24 channels) into a 5 × 5 matrix (25 channels). Consequently, a complete 5 × 5 3DPI is available for each sample. Eq. 2 shows the arrangement of a 5 × 5 tactile sensor.

$$\begin{pmatrix} 1 & 6 & 11 & 16 & 21 \\ 2 & 7 & 12 & 17 & 22 \\ 3 & 8 & 13 & 18 & 23 \\ 4 & 9 & 14 & 19 & 24 \\ 5 & 10 & 15 & 20 & 25 \end{pmatrix}, \tag{2}$$

where the numbers in the matrix represent the numbers of channels.

	$\overline{errorT_2}$
All subjects	0.058 ± 0.061
Left hands	0.053 ± 0.052
Right hands	0.065 ± 0.068
Male	0.059 ± 0.060
Female	0.057 ± 0.067
Non-hypertensive subjects	0.052 ± 0.048
Hypertensive subjects	0.060 ± 0.063

2.3 Pressing offset evaluation

In this article, the errors between each channel and the best channel in 3DPIs are determined to evaluate the pressing offsets. Following preprocessing, channels with the maximum amplitude are automatically selected as the best channels for each sample. Using these best channels as a benchmark, a stringent manual screening of the samples is conducted by a cardiovascular expert, who also provided manual annotations for the P_2 position. The expert annotation serves as the gold standard for P_2 localization. In this section, $errorT_2$, the average $errorT_2$ ($\overline{errorT_2}$), and $errorT_2$ Stacked Surface ($errorT_2SS$) are proposed to evaluate the pressing offsets.

By performing manual annotations for P_2, the T_2 across all channels are obtained for each sample. Subsequently, for each sample, the error between each channel and the maximum channel, representing the $errorT_2$ for each channel, are calculated (see Eq. 3). Then, $\overline{errorT_2}$ across all channels for all subjects are calculated (see Eq. 4). Based on the specifications of the 5 × 5 tactile sensors, we arrange the $errorT_2$ of 25 channels and ultimately obtain the $errorT_2$ Surface ($errorT_2S$) matrix for each sample. The $errorT_2$ can assess the discrepancy between T_2 of a single channel and the best channel, while $errorT_2S$ evaluates the pressing offset for a sample. $ErrorT_2S$ can also assess the discrepancy between T_2 of each channel and the best channel in the spatial domain, thereby facilitating an understanding of the distribution of pulse extraction center points.

$$errorT_2(n,c) = |T_{2C}(n) - T_{2best}(n)|, \qquad (3)$$

where c represents the number the channel, $T_{2C}(n)$ is T_2 in the cth channel of sample n, $T_{2best}(n)$ is T_2 in the best channel of sample n.

$$\overline{errorT_2}(n) = \frac{\sum_c^\Gamma |T_{2C}(n) - T_{2best}(n)|}{\Gamma}, \qquad (4)$$

where Γ is 25, the number of all channels in this study.

To investigate the offset degree of the robotic finger pressing process during data collection, the $errorT_2S$ of all samples are stacked to construct the $errorT_2SS$. Algorithm 1; Figure 4 demonstrate the construction process of the $errorT_2SS$. Firstly, a 9 × 9 zero matrix is created to represent the 9 × 9 channel matrix as the base. Subsequently, the best channels of each $errorT_2S$ are aligned with the center channel of the base for stacking. Lastly, the weighted $errorT_2$ are calculated for each channel within the 9 × 9 base (see Eqs 5, 6). The obtained weighted $errorT_2$ constitute the $errorT_2SS$ matrix.

$$Weighted\ errorT_2(c) = \sum_n^N \omega_n \cdot errorT_2(n,c), \qquad (5)$$

ω_n represents the weight in cth channel, which is defined as:

$$\omega_n = \begin{cases} 1, errorT_2(n,c)_{9\times9} > 0 \\ 0, errorT_2(n,c)_{9\times9} = 0 \end{cases}, \qquad (6)$$

where $errorT_2(n,c)_{9\times9}$ denotes the cth $errorT_2$ that $errorT_2S$ of a sample is stacked and aligned to the center channel of the 9 × 9 base.

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Input: T₂: time of P₂;
S: pulse signals, S_C is the pulse signal of the
cth channel;
N: number of samples, n is the nth sample;
M: Arrangement of the 5 × 5 tactile sensor
Output: errorT₂SS: errorT₂ Stacked Surface matrix
  1:   Initialize an empty errorT₂ Surface
       (errorT₂S) matrix
  2:   for each sample in n do
  3:     extract channel with maximum amplitude
         as S_best(n)
  4:     for each channel in all channels of
           sample n do
  5:       calculate errorT₂ for S_C(n) using Eq. 3
  6:     end for
  7:     arrange all errorT₂(c) of 25 channels
           according to M to form errorT₂S (n)
  8:   end for
  9:   Initialize a 9 × 9 zero matrix as base
 10:   for each errorT₂S(n) do
 11:     align best channels with the center
           channel of the base
 12:     stack the aligned errorT₂S(n) on top
           of the base
 13:   end for
 14:   calculate the weighted errorT₂ for each
         channel using Eq. 5
 15:   form errorT₂SS matrix using the
         weighted errorT₂
```

Algorithm 1. Construction process of the errorT₂SS.

3 Results

3.1 Quantitative analysis of all subjects

Figure 5 displays the $errorT_2SS$ and weighted $errorT_2$–distance relation for all subjects. Figures 5A, B present the heat map and 3D bar of the $errorT_2SS$ for all subjects, respectively. The $errorT_2SS$ demonstrates a central low and peripheral high pattern. The further away from the center point, the higher the weighted $errorT_2$ trend. Furthermore, an upward trend is observed at both ends of the axis corresponding to the blood flow direction, with higher weighted $errorT_2$ as distance from the vessel increases. The central value is 0, as it represents that the central channel covers the best channels of all samples. Figures 5C, D illustrate the weighted $errorT_2$–distance

FIGURE 6
The errors between each channel and the best channel for left and right hands: **(A)** The normalized 3DPI in T_2 of all samples of left hands; **(B)** The normalized 3DPI in T_2 of all samples of right hands; **(C)** The heat map of errorT$_2$SS of all samples of left hands; **(D)** The heat map of errorT$_2$SS of all samples of right hands; **(E)** The 3D bar of errorT$_2$SS of all samples of left hands; **(F)** The 3D bar of errorT$_2$SS of all samples of right hands. The red arrow indicates the direction of blood flow.

boxplots for all subjects. The boxplots indicate nonlinear relationships between the increase in distance and the corresponding increase in errorT$_2$. For every 1 mm increase in distances between sensing elements and center sensing elements, the weighted errorT$_2$ in the radial direction escalates by 4.87%. The weighted errorT$_2$ tends to be stable in the axial direction. As the distances from the center channel increase, the volatilities of the errorT$_2$ become more pronounced. When the distance is greater than 3.42 mm, the radial weighted errorT$_2$ experiences a sudden increase.

Table 2 shows the $\overline{errorT_2}$ on different control groups in this study. In summary, the $\overline{errorT_2}$ of all subjects is 0.058. The $\overline{errorT_2}$ for left-handed subjects and non-hypertensive subjects are relatively lower, at 0.053 and 0.052. In comparison, right-handed subjects, males, and hypertensive subjects exhibit higher $\overline{errorT_2}$ of 0.065, 0.059, and 0.060, respectively. With regard to gender, male subjects have a slightly lower $\overline{errorT_2}$ than females, with values of 0.059 and 0.057.

3.2 Comparative study for all control groups

3.2.1 Left hands vs. Right hands

Figure 6 displays the errors between each channel and the best channel of left and right hands. The errorT$_2$SS exhibits a central low and peripheral high pattern for both hands. Moreover, an upward trend is observed at both ends of the axis corresponding to the blood flow direction. It can be observed that the error distributions for both hands show a subtle difference compared to the average error (Figure 5) distribution for all subjects. The boxplots in Figure 7 indicate that for every 1 mm increase in distance, the weighted errorT$_2$ in the radial direction for left and right hands escalate by 4.55% and 5.04%, respectively. When the distance is greater than 3.42 mm, the radial weighted errorT$_2$ for the left and right hands experience sudden increases.

3.2.2 Male vs. Female

Figure 8 illustrates the errors between each channel and the best channel of male and female subjects. The errorT$_2$SS shows a central

FIGURE 7
The weighted errorT$_2$−distance boxplots for left and right hands: **(A)** The radial weighted errorT$_2$−distance boxplot of left hands, *x*-axis represents the distance between sensing elements and center sensing elements, *y*-axis represents the radial weighted errorT$_2$, a unit of the *x*-axis represents 1.71 mm; **(B)** The radial weighted errorT$_2$−distance boxplot of right hands, a unit of the *x*-axis represents 1.71 mm; **(C)** The axial weighted errorT$_2$−distance boxplot of left hands, a unit of the *x*-axis represents 1.25 mm; **(D)** The axial weighted errorT$_2$−distance boxplot of right hands, a unit of the *x*-axis represents 1.25 mm. A sensing element is a channel in a sensor. The red arrow indicates the direction of blood flow.

low and peripheral high pattern for both male and female, with an upward trend at both ends of the axis corresponding to blood flow direction. It is noteworthy that the right-most channels of the errorT$_2$SS for female samples exhibit data missing, suggesting that no channels were stacked on the base channels during the stacking of errorT$_2$S for female subjects. The weighted errorT$_2$ in the upper-right corner of the errorT$_2$SS for females are relatively greater, which may be caused by outlier values. Figure 9 shows that for every 1 mm increase in distance, the weighted errorT$_2$ in the radial direction for male and female subjects rise by 4.86% and 3.98%, respectively. When the distance is greater than 3.42 mm, the radial weighted errorT$_2$ for the male subjects experiences a sudden increase. Since the data in the right-most channels is missing, there are only 8 distance groups in Figure 9B.

3.2.3 Non-hypertensive vs. Hypertensive

Figure 10 displays the errors between each channel and the best channel for non-hypertensive and hypertensive subjects. The errorT$_2$SS exhibits a pattern of central decrement and peripheral increment, with an ascending trend at both extremities of the axis

corresponding to the direction of blood flow. It can be inferred that the errorT$_2$SS for non-hypertensive subjects is more evenly distributed compared to hypertensive patients overall, whereas the errorT$_2$SS for hypertensive patients exhibits smaller errors along the arterial axis. Figure 11 indicates that for every 1 mm increase in distance, the weighted errorT$_2$ in the radial direction for non-hypertensive and hypertension subjects rise by 4.94% and 5.04%, respectively. When the distance is greater than 3.42 mm, the radial weighted errorT$_2$ for the non-hypertensive and hypertension subjects experience sudden increases.

4 Discussion

This study discovers the pressing offsets in multi-channel pulse signals and analyzes the relationship between the pressing offsets and T$_2$ by qualifying the pressing offsets in pulse signal acquisition. First, we employ a data acquisition system to obtain 3DPIs from the subjects. Subsequently, the errors between each channel and the best channel are determined. The error T$_2$ Stacked Surface (errorT$_2$SS)

FIGURE 8
The errors between each channel and the best channel for male and female subjects: **(A)** The normalized 3DPI in T_2 of all samples of male subjects; **(B)** The normalized 3DPI in T_2 of all samples of female subjects; **(C)** The heat map of errorT_2SS of all samples of male subjects; **(D)** The heat map of all samples of female subjects; **(E)** The 3D bar of errorT_2SS of all samples of male subjects; **(F)** The 3D bar of errorT_2SS of all samples of female subjects. The red arrow indicates the direction of blood flow.

and the average error T_2 ($\overline{errorT_2}$) are implemented to qualify the pressing offsets in the tactile sensor. Finally, the subjects are divided into multiple control groups, and the results are compared and analyzed.

Figures 5, 6, 8, 10 display the error between each channel and the best channel for all control groups. All errorT_2SS in these figures exhibit a central low and peripheral high pattern. In each errorT_2SS, the further away from the central point, the more upward the trend for all channels. The comparative study shows similar patterns for all subjects and control groups, revealing that our qualifications meet the true conditions of arterial pulse signals and the characteristics of the human radial arteries. The center of each errorT_2SS reflects the offsets of the best channels, which are the smallest among all channels. The positions of the best channels align with the center of pressure on the arteries. Furthermore, the error values increased as distance from the artery increased, particularly at the axial ends of the blood flow direction. In Figure 8, data missing is existed in the rightmost column of the errorT_2SS for female subjects. Considering the

sample size of female subjects in this study, the errorT_2S of female samples may not thoroughly cover the entire 9×9 base matrix. Another possible reason is that the arteries of women exhibit more diminutive diameters (Xu et al., 2017; Deora et al., 2022) and are more difficult to adapt to the robotic fingertips. The inspiration from the results is selecting sensors with tiny sensing elements for pulse signal acquisition for female subjects. Figure 10 shows that the error distribution of non-hypertensive subjects is more uniform compared to hypertensive patients, while the errorT_2SS of hypertensive patients has lower errors in the arterial axis. Compared to hypertensive patients, non-hypertensive subjects have lower vascular stiffness (Su et al., 2016; Zhang et al., 2021). Subsequently, during the pressing process of the robotic finger, the offsets might occur less.

The boxplots in Figures 7, 9, 11 indicate nonlinear relationships between the increase in distance and the corresponding increase in errorT_2. For every 1 mm increase in distances between sensing elements and center sensing elements, the weighted errorT_2 in the radial direction escalates by 4.87%. The weighted errorT_2 escalations for left hands/right

FIGURE 9
The weighted errorT$_2$−distance boxplots for male and female subjects: **(A)** The radial weighted errorT$_2$−distance boxplot of male subjects, x-axis represents the distance between sensing elements and center sensing elements, y-axis represents the radial weighted errorT$_2$, a unit of the x-axis represents 1.71 mm; **(B)** The radial weighted errorT$_2$−distance boxplot of female subjects, a unit of the x-axis represents 1.71 mm; **(C)** The axial weighted errorT$_2$−distance boxplot of male subjects, a unit of the x-axis represents 1.25 mm; **(D)** The axial weighted errorT$_2$−distance boxplot of female subjects, a unit of the x-axis represents 1.25 mm. A sensing element is a channel in a sensor. The red arrow indicates the direction of blood flow.

hands, male/female, and non-hypertensive/hypertensive are 4.55%/5.04%, 4.86%/3.98%, and 4.94%/5.04%, respectively. The clinical insights derived from these distinct results indicate that each clinical population possesses distinct physiological characteristics. Therefore, when acquiring pulse signals, it is essential to employ appropriate collection and measurement techniques to mitigate pressing offsets. For all control groups, when the distance is larger than 3.42 mm, the weighted radial errorT$_2$ experience sudden increases for all subjects and control groups. This result can assist and guide operators in pressing processes. In clinical practice, we recommend the pressing offset of sensors not exceed 3.42 mm, which can adjust by qualifying the evaluation metrics. The weighted errorT$_2$ tends to be stable in the axial direction. To our knowledge, the reason is that axial direction is the direction of the blood flow. The changes in the mechanical environment are different between axial and radial of the arterial smooth muscle (Messas et al., 2013; Rothermel et al., 2020).

When the robotic fingers of pulse acquisition devices apply pressing, offset may occur, potentially affecting measurement outcomes. In scenarios involving single or few-channel sensors, such offsets have more substantial impacts on measurement results. In such cases, the operators may face difficulties in establishing whether the pressing process is accompanied by offsets. Such hindrance could potentially detract physicians from making accurate assessments of cardiovascular conditions in patients. This study detects pressing offsets in radial arterial pulse signals and explores the solution to prevent pressing offsets. In the analysis of this study, the errorT$_2$ enables the quantification and evaluation of 3DPI, thus allowing for the determination of the offset degree during the pressing process and subsequent correction. With adequate sensor channels, we can implement the measurements in this study to qualify and evaluate the pressing offsets. However, when the number of sensor channels is one or few, it is hard to use the measurements to determine the pressing offset, and the operators face difficulties in establishing whether the pressing process is accompanied by offsets. Furthermore, only adequate sensor channels can help operators obtain more accurate clinical and physiological parameters, which are essential for the further assessment and diagnosis of physiological conditions in subjects. This is undoubtedly of great importance in clinical practice. Therefore, we highlight that increasing the sensor channels is crucial for achieving quantitative offset assessment.

Furthermore, the arterial conditions are compared and analyzed under different circumstances. This study employs three control groups:
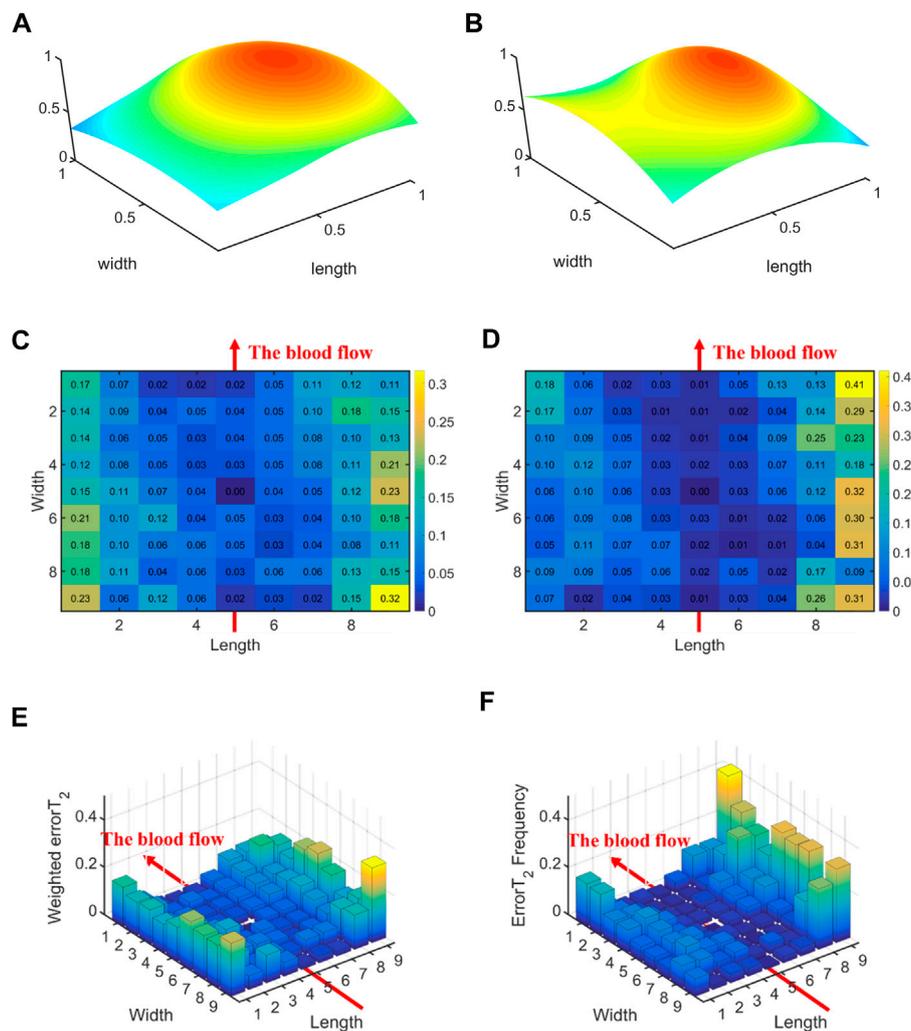
FIGURE 10
The errors between each channel and the best channel for non-hypertensive and hypertension subjects: **(A)** The normalized 3DPI in T_2 of all samples of non-hypertensive subjects; **(B)** The normalized 3DPI in T_2 of all samples of hypertension subjects; **(C)** The heat map of errorT$_2$SS of all samples of non-hypertensive subjects; **(D)** The heat map of errorT$_2$SS of all samples of hypertensive subjects; **(E)** The 3D bar of errorT$_2$SS of all samples of non-hypertensive subjects; **(F)** The 3D bar of errorT$_2$SS of all samples of hypertensive subjects. The red arrow indicates the direction of blood flow.

left hands/right hands, male/female, and non-hypertensive/hypertensive subjects. During the pressing process, the tactile sensors of the pulse signal acquisition instrument are similarly influenced by the arteries of both hands. In contrast, the non-hypertensive/hypertensive subjects control group demonstrates a higher arterial stiffness in the hypertensive subjects, which readily affects the pressing process of the robotic finger (Milkovich et al., 2022). However, when the number of channels is limited to a single or few, analyzing these situations becomes challenging. Consequently, the most crucial aspect for analyzing the arterial characteristics of the subjects through sensors is increasing the sensor channels.

5 Conclusion

In scenarios involving single or few-channel sensors, pressing offsets have substantial impacts on measurement results. By detecting whether there are any offsets occurring during the

pressing process, operators can adjust the pressing position to ensure the acquisition of 3DPIs that accurately reflect the arterial conditions. This study discovers the pressing offsets in multi-channel pulse signals and analyzes the relationship between the pressing offsets and T_2 using a method to qualify the pressing offsets in pulse signal acquisition. First, we design a data acquisition system to capture 3DPIs from the subjects. Second, the errorT$_2$ Stacked Surface (errorT$_2$SS) and the average error T_2 ($\overline{errorT_2}$) are proposed to qualify the pressing offsets in the tactile sensors. Finally, the subjects are divided into several control groups for subsequent analysis. The comparative study for errorT$_2$SS exhibits a central low and peripheral high pattern. Furthermore, the error values increased as distance from the artery increased, particularly at the axial ends of the blood flow direction. For every 1 mm increase in distances between sensing elements and center sensing elements, the weighted errorT$_2$ in the radial direction escalates by 4.87%. When the distance is greater than 3.42 mm, the weighted radial errorT$_2$ experience sudden increases for all

FIGURE 11
The weighted errorT$_2$−distance boxplots for non-hypertensive and hypertensive subjects: **(A)** The radial weighted errorT$_2$−distance boxplot of non-hypertensive subjects, x-axis represents the distance between sensing elements and center sensing elements, y-axis represents the radial weighted errorT$_2$, a unit of the x-axis represents 1.71 mm; **(B)** The radial weighted errorT$_2$−distance boxplot of hypertensive subjects, a unit of the x-axis represents 1.71 mm; **(C)** The axial weighted errorT$_2$−distance boxplot of non-hypertensive subjects, a unit of the x-axis represents 1.25 mm; **(D)** The axial weighted errorT$_2$−distance boxplot of non-hypertensive subjects, a unit of the x-axis represents 1.25 mm. A sensing element is a channel in a sensor. The red arrow indicates the direction of blood flow.

subjects and control groups. The weighted errorT$_2$ tends to be stable in the axial direction. The subjects in this study are middle-aged and elderly subjects aged 40–80 years, leading to a potential lack of representativeness. In the future, several enhancements may be contemplated for application in subsequent research. In the end, it remains imperative to highlight the necessity of increasing the sensor channels.

6 Limitation

Although this study discovers pressing offsets in radial pulse signal acquisition, some limitations should be reported. The subjects in this study are middle-aged and elderly subjects aged 40–80 years, leading to a potential lack of representativeness. The subjects aged 40–80 years may hinder the generalization of the methods presented in this study to younger subjects. In addition, the presence of missing data in errorT$_2$SS for female subjects is due to the weighted errorT$_2$ absence of these regions, which may potentially affect the analysis of pressing offsets in female subjects, thereby hindering the acquisition of accurate conclusions. More young subjects and female subjects should be

included. In terms of prospects, several enhancements may be contemplated for application in subsequent research. For instance, broaden the age range of the sample population and include more control groups, such as subjects with other diseases, before and after exercise, and different postures, to make the research more universally applicable to the physical characteristics of blood vessels. In addition to expanding the composition of the sample, incorporating real-time measurement adjustments based on pressing offsets could serve as a potential future research enhancement.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by the National Cheng Kung University Hospital (Approval Number: B-ER-103-

263). The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

CC: Methodology, Writing–original draft, Writing–review and editing. ZC: Methodology, Validation, Writing–review and editing. HL: Methodology, Writing–review and editing. BP: Data curation, Supervision, Writing–review and editing. YH: Validation, Writing–review and editing. XX: Supervision, Writing–review and editing. HX: Data curation, Writing–review and editing. XL: Data curation, Writing–review and editing.

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Conflict of interest

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