Reduction of Interference in Oscillometric Arterial Blood Pressure Measurement Using Fuzzy Logic

Chin-Teng Lin*, *Senior Member, IEEE*, Shing-Hong Liu, Jia-Jung Wang, and Zu-Chi Wen

***Abstract*—In oscillometry, oscillation amplitudes (OAs) embedded in the cuff pressure are drastically affected by a variety of artifacts and cardiovascular diseases, leading to inaccurate arterial blood pressure (ABP) measurement. The purpose of this paper is to improve the accuracy in the arterial pressure measurement by reducing interference in the OAs using a recursive weighted regression algorithm (RWRA). This method includes a fuzzy logic discriminator (FLD) and a recursive regression algorithm. The FLD is used to reduce the effect of artifacts caused by measurement motion disturbance or cardiovascular diseases, and to determine the truthfulness of the oscillation pulse. According to the truth degree, the relationship between the cuff pressure and OA is reconstructed using the regression algorithm. Because the regression method must utilize inverse matrix operation, which will be difficult to implement in an automatic or ambulatory monitor, the recursive regression method is proposed to solve this problem. To test the performance of this RWRA, 47 subjects underwent the ABP measurement using both the auscultation and the oscillometry combined with the RWRA. It was found that the average difference between the pooled blood pressures measured by the auscultation and those by the oscillometry combined with the RWRA was found to be only 4.9 mmHg. Clinical results demonstrated that the proposed RWRA is more robust than the traditional curve fitting algorithm (TCFA). We conclude that the proposed RWRA can be applied to effectively improve the accuracy of the oscillometric blood pressure measurement.**

***Index Terms*—Blood pressure, fuzzy logic, oscillation, oscillometry, regression.**

I. INTRODUCTION

MOST commercial automatic blood-pressure monitors primarily apply either the auscultatory or the oscillometric methods for measurement. Both of these methods utilize an occlusive cuff, as an external pressure source, wrapping around a subject's upper arm to disclose the systolic and diastolic pressures within 30–60 s. In the deflation period, the fluctuating wall of the blood vessel slightly alters the blood pressure, giving rise to oscillations in the cuff pressure. A specific pattern will be shown when the occluding cuff pressure is gradually reduced from above systolic to below diastolic values. In the oscillometric method, because a reflective notch waveform appears in a raw blood pressure waveform, the technique of maximum change of positive slope is used to find the peak values of oscillation waveform which are considered as the oscillation amplitudes (OAs). The OA and the cuff pressure are then used to determine the mean arterial, systolic and diastolic pressures. Fig. 1 shows the relative position of the systolic and diastolic pressures on the patterns of cuff pressure and oscillation waveform. It is now generally accepted that a maximum cuff pressure oscillation occurs when the occlusive cuff pressure is equal to the mean arterial pressure (MAP) [1]–[3]. Systolic pressure is the pressure where the OA is a systolic ratio of the maximum oscillation in the period of high cuff pressure. In contrast, diastolic pressure is the pressure where the OA is a diastolic ratio of the maximum oscillation in the period of low cuff pressure.

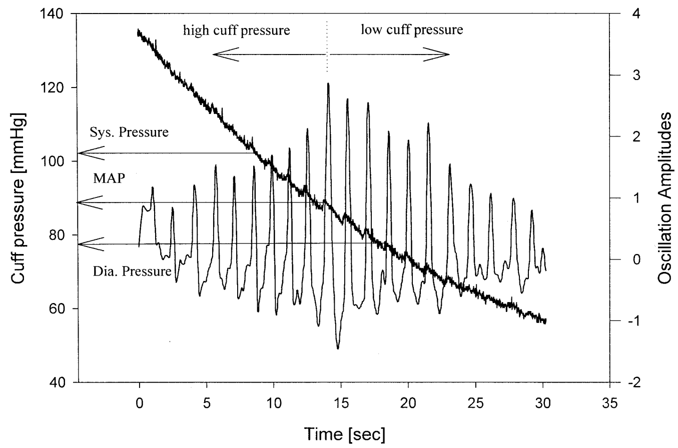

Fig. 1. The systolic (Sys.) and diastolic (Dia.) pressures detected from an oscillation pattern with the oscillometric method, where the dense decreasing line represents the cuff pressure (P_c), the thin line represents the oscillation signal of cuff pressure, and MAP means the mean arterial pressure.

There are two major shortcomings in applying the oscillometry. One is that an artifact from the patient's motion will contaminate the actual OAs, resulting in a change in the OAs. The other is that a large number of cardiovascular diseases, such as arrhythmia, will lead to an irregular OA. Due to these two drawbacks, it is difficult to produce a smooth curve representing the authentic envelope of the OAs. This makes the blood pressure measurement inaccurate. Therefore, a variety of techniques have been proposed to overcome the disturbance of the OA profile and to improve the accuracy in blood pressure measurement [4]–[6]. Most of them employed smoothing (or averaging) maneuvers or pulse matching algorithms to reject

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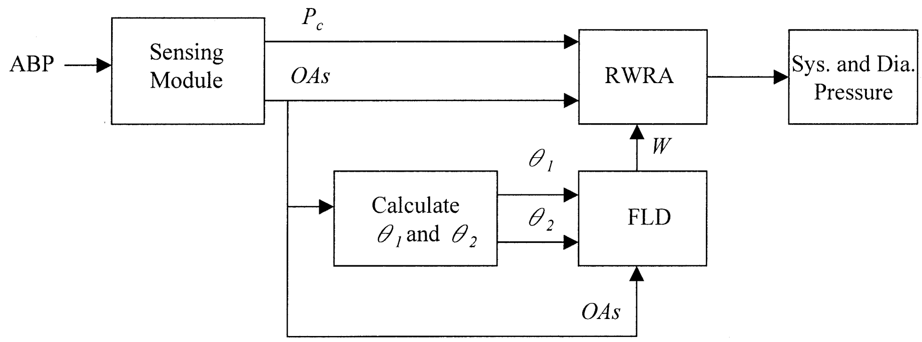

Fig. 2. Block diagram of the proposed oscillometric measurement system, where input is the ABP, P_c is cuff pressure, θ_1 is the angle formed by three contiguous OAs [see Fig. 3(a)], θ_2 is the angle formed by five contiguous OAs [see Fig. 3(a)], and W is a weighting factor.

the motion artifact [7]. Also, the Kalman filter has been investigated to conquer these problems [8], [9]. Another approach to determining the isolated pressure and the rate of pressure change has been proposed, in which the brachial artery pulsation signal obtained by an oscillometric methodology was incorporated [10].

Recently, fuzzy logic has been widely applied in the biomedical control and feature extraction [11]–[14]. One of the advantages of fuzzy logic is that it can be established empirically without explicit mathematical models of nonlinear physiological systems [15], [16]. Also, since fuzzy logic is based on linguistic rules, it is not difficult to implement a feature extraction system with fuzzy logic. In this paper, we shall apply fuzzy logic theory to reduce the interference in oscillometric arterial blood pressure (ABP) measurement.

In the oscillometry, the measured OAs contain a large amount of physiologic disturbance inherently, so reconstructing the relationship between the cuff pressure and OA is a challenging task. To solve this problem in this paper, we design a fuzzy logic discriminator (FLD) to effectively remove the interference in the OAs due to different kinds of artifacts. We then apply a regression algorithm based on the weighting factors determined by the FLD to reconstruct the relationship between the cuff pressure and OA. A recursive computation method is used in the linear regression algorithm to form the recursive weighted regression algorithm (RWRA) for reconstructing the OA pattern. There are two reasons for using the recursive computation method in the linear regression algorithm. One is that there are about 30 to 40 heartbeats during the measurement period, so the rank of the corresponding regression matrix is about 30 to 40. In a commercial automatic blood pressure monitor, the inverse operation of a high-rank matrix is difficult to program in a single-chip processor. The other reason is to reduce the measurement time. If the regression matrix is used to calculate the parameter vector directly, then the program must wait for the finish of the measurement procedure to start the mathematical calculations, so that the real-time blood pressure monitor is difficult to obtain. In RWRA, each OA of a heartbeat is detected and immediately used to update the parameter vector to fit the current measured data. This can largely decrease the final mathematical calculation time and speed up the whole measurement procedure. The systolic and diastolic pressures are detected from the new relationship between the cuff pressure and OA, which is constructed by the RWRA. Extensive clinical tests have been done to verify the performance of our designed algorithm. The outcomes measured by the proposed RWRA technique will be further compared with those measured by the mercury column sphygmomanometer performed by the professional nurse.

This paper is organized as follows. In Section II, an FLD and a recursive regression method are designed for reducing the redundancy of OA. In Section III, the practically clinical measurement for verifying the proposed algorithm, and the statistic method for comparing the accuracy and reliability of the estimated blood pressures are presented. Discussions and conclusions are made in Section IV.

II. Fuzzy-Logic-Based Recursive Weighted Regression Algorithm

The oscillometry cannot provide the accurate systolic and diastolic pressures once the disturbances resulting from arm's motion, tremor or cardiovascular abnormalities occur during the measurement period. This is because these disturbances will greatly distort the original OAs, leading to a change in the specific OAs that correspond to the systolic and diastolic pressures, respectively. Therefore, this paper focuses on investigating how to extract the features of disturbance from the measured OAs. The degree of closeness between the corrupted and original OAs is represented by a weighting factor. In general, an OA with a smaller weighting factor contributes less to the reconstruction of the OA profile.

Fig. 2 shows the block diagram of the proposed measurement system. The whole system includes the sensing module, a feature detector of disturbance, an FLD, and an RWRA. The sensing module of the oscillometric measurement system, including pressure sensor, pumping air motor, and valve, simultaneously record cuff pressure (P_c) and the corresponding oscillation waveforms. The peak values on the oscillation waveform are then detected as the OAs. The disturbance characteristics of the OA, θ_1 and θ_2 defined later, are then extracted from the OAs' pattern. The FLD uses these parameters, including θ_1, θ_2, and OAs to determine a weighting factor to represent the OAs truthfulness, and the RWRA uses this weighting factor along with the cuff pressure and OAs to reconstruct the shape of change in OA over cuff pressure. The systolic and diastolic pressures are then detected based on this reconstructed relationship.

In the sensing module of Fig. 2, a silicon membrane pressure transducer (SenSym, SCX05DNC) is used to measure the cuff pressure. The sensed analog cuff pressure signal (P_c) is further processed using a band-pass filter with cut-off frequencies of 0.5–3 Hz to produce the oscillation signal (see Fig. 1). The cuff pressure signal and the oscillation signal are then converted to digital signals using a 12-bit A/D converter. Then the technique of maximum change of positive slope is used to find the oscillation peaks (OAs) on the oscillation signal [17]. During the peak detection process, the oscillation signal slope is measured periodically at a rapid rate, and unless the slope meets some predetermined criteria, the peaks will be measured and compared. The measured cuff pressure and OA are then used in other functional blocks of Fig. 5 as detailed in Section II-A and Section II-B.

A. FLD for Disturbance Estimation

In several previous studies, the relationship between the cuff pressure (P_c) and OA has been investigated when the cuff was deflated [18], [19]. But how to reject the noise from the acquired data becomes a practical challenge. Therefore, it is necessary to explore an efficient approach for the disclosure of the reliable relationship between the cuff pressure and OA. In this section, an FLD is designed to reduce the effect of artifacts and to determine the truthfulness of the OA corresponding to individual heart beat. Reasonably, the more artifacts contained in the oscillation pulses, the lower degree of truthfulness that the measured OA represents in extracting the shape of change in OAs over cuff pressure. According to the fuzzy logic theory, the degree of the truthfulness for the OAs can be considered as the weighting factor in identifying the true measured targets. In general, if an OA's truthfulness degree is close to zero, the OA plays an inferior role in the reconstruction of the oscillometric pattern.

In Fig. 3, four typical oscillation waveforms of normal and abnormal cardiovascular functions, corresponding to the normal subject without cardiovascular disease and the subjects with arrhythmia, atherosclerosis, and hypertension respectively, are used to describe how to extract the disturbance characteristics from the OA patterns and construct the fuzzy logic rules in the FLD. Fig. 3(a) shows a normal oscillation waveform from a young man whose age, weight, and blood pressure (systolic/diastolic) are 26 years, 70 Kg, and 102/64 mmHg, respectively. Fig. 3(b) shows an oscillation waveform of arrhythmia from an old man with cardiac arrhythmia whose age, weight, and blood pressure are 85 years, 74 Kg and 148/56 mmHg, respectively. This waveform appears to contain periodic irregular heart beats. Fig. 3(c) shows an oscillation waveform of atherosclerosis from an old man with atherosclerosis whose age, weight, and blood pressure are 68 years, 67 Kg, and 140/76 mmHg, respectively. This waveform contains a wider range in the MAP's neighborhood. Fig. 3(d) shows an oscillation waveform of hypertension from an old man with hypertension whose age, weight, and blood pressure are 63 years, 80 Kg, and 170/96 mmHg, respectively. This waveform appears to have waveform shifting to the high pressure. We can find that the envelopes of the oscillation waveforms of atherosclerosis and hypertension are similar to those of normality. Therefore, we only illustrate the ways of extracting the disturbance characteristics from the oscillation waveforms of normality and arrhythmia in the following.

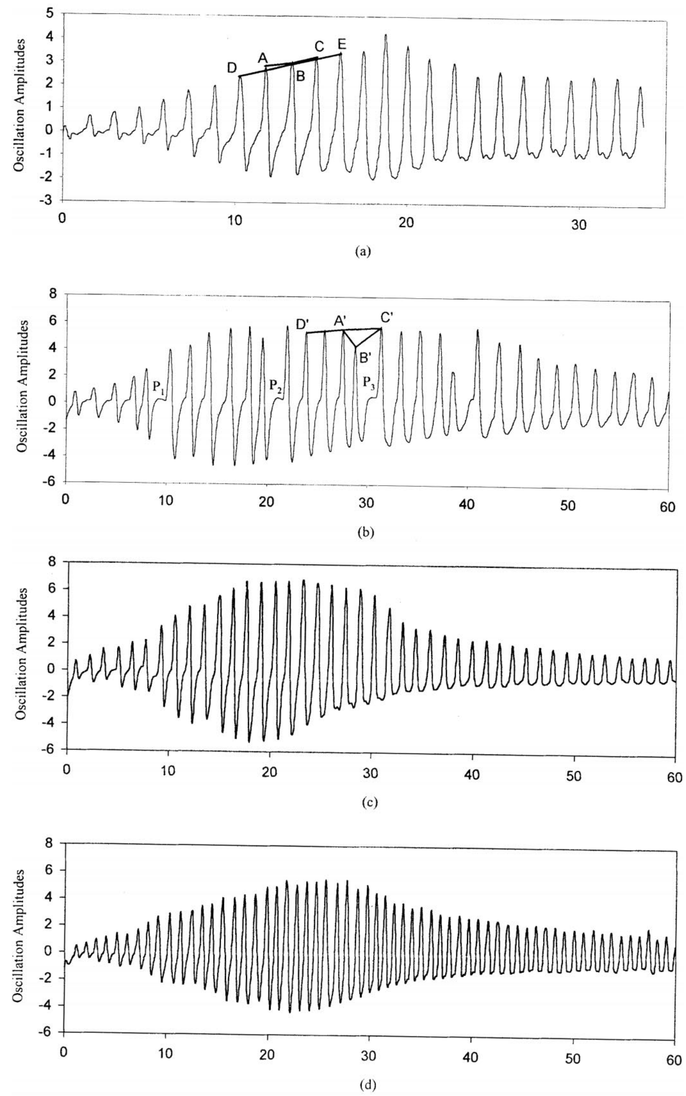

Fig. 3. (a) The oscillation waveform from a subject with normal cardiovascular function. (b) The oscillation waveform from a subject with cardiac arrhythmia. (c) The oscillation waveform from a subject with atherosclerosis. (d) The oscillation waveform from a subject with hypertension.

In the normal oscillometric pattern, it is obvious that an angle (θ_1), close to 180°, is formed among one specific OA and its two contiguous OAs [e.g., $\theta_1 = \angle$ ABC in Fig. 3(a)], except the angle corresponding to the maximal OA. This is also true for the angle, θ_2, formed by five contiguous OAs [e.g., $\theta_2 = \angle$ DBE in Fig. 3(a)]. But, if one OA corresponding to an arrhythmic beat, the angle formed by three contiguous OAs, θ_1, will become smaller [e.g., $\theta_1 = \angle$ A′B′C′ in Fig. 3(b)]. However, even in this case, the angle formed by five contiguous OAs, θ_2, is possibly close to 180° [e.g., $\theta_1 = \angle$ D′A′C′ in Fig. 3(b)]. Therefore, the FLD is designed to have three inputs, including the OA, the angle formed by three contiguous OAs (θ_1), and the angle formed by five contiguous OAs (θ_2). If these angles are obtuse angels, their supplementary angles will be calculated. This design ensures θ_1 and θ_2 being acute angles. The fuzzy term set for the input OA is composed of three membership functions: MAX, MID and MIN. These fuzzy terms are defined by means of triangular functions in the [0 7] subset of real numbers.

The fuzzy term set for θ_1 or θ_2, also using triangular functions defined in the [0° 180°] subset of real numbers, includes four membership functions: BEST, GOOD, WORSE, and WORST. The triangular membership function, $\mu(x)$, $x = \theta_1, \theta_2$, or OA, is defined by

$$\mu_i(x) = \begin{cases} 0, & x < l_i \\ \dfrac{x - l_i}{m_i - l_i}, & l_i \le x < m_i \\ \dfrac{-x + n_i}{n_i - m_i}, & m_i \le x < n_i \\ 0, & x \ge n_i \end{cases} \tag{1}$$

where l_i and n_i indicate the defined internal $[l_i\ n_i]$ of fuzzy term i, and m indicates the defined center of fuzzy term i. In other words, m_i in (1) represents the center of the triangular membership function whose value is one at m_i, and the functions $(x - l_i)/(m_i - l_i)$ and $(-x + n_i)/(n_i - m_i)$ define the left spread and right spread of the triangle-shape function $\mu_i(x)$ on the internals $[l_i, m_i]$ and $[m_i, n_i]$, respectively. The output of the FLD is the weighting factor W, which represents the degree of truthfulness of the current OA. The fuzzy term set for the weighting factor has four fuzzy terms with singleton type: $X0 = 0$, $X0.4 = 0.4$, $X0.7 = 0.7$, and $X1 = 1$.

There are two major concepts in constructing the fuzzy logic rules in the FLD. First, we can find from Fig. 3(b) that the angle $\theta_1 = \angle$ A′B′C′ becomes smaller, when the OA is present in the condition that the cuff pressure is equal to MAP, or is contaminated by undesired artifacts. Therefore, the input OA can help the FLD to discriminate whether the heart beat belongs to a normal or abnormal beat. Second, also from the observation on Fig. 3(b), the contiguous OAs of the abnormal heart beats will have $\theta_1 = \angle$ A′B′C′ smaller than $\theta_2 = \angle$ D′A′C′, when the OA is in an ascending or descending procedure. According to these observations, 38 fuzzy rules are designed to form the rule set of the FLD. The individual rule-based inference process is supervised by computing the degree of match between the fuzzified input values and the fuzzy set describing the meaning of the rule-antecedent. Fig. 4 shows the distribution of all the designed fuzzy rules, where ●, ▼, ■, and ♦ represent the fuzzy singleton output 1, 0.7, 0.4, and 0, respectively. Four representative fuzzy rules are listed below:

If OA is MAX and θ_1 is WORST and θ_2 is WORSE, THEN W is 1.

If OA is MID and θ_1 is GOOD and θ_2 is BEST, THEN W is 0.7.

If OA is MIN and θ_1 is WORSE and θ_2 is GOOD, THEN W is 0.4.

If OA is MIN and θ_1 is WORST and θ_2 is WORSE, THEN W is 0.

As expressed in (2), the output μ is produced by clipping the fuzzy membership functions, and the possibility distribution function is then found by applying the Mamdani's max–min operator [15]

$$\mu_W(w) \equiv \bigvee_{i}^{r} \{[\mu_{\mathrm{OA}_i}(u_0) \wedge \mu_{\theta_1 i}(v_0) \wedge \mu_{\theta_2 i}(y_0)] \wedge \mu_{Wi}(w_0)\} \tag{2}$$

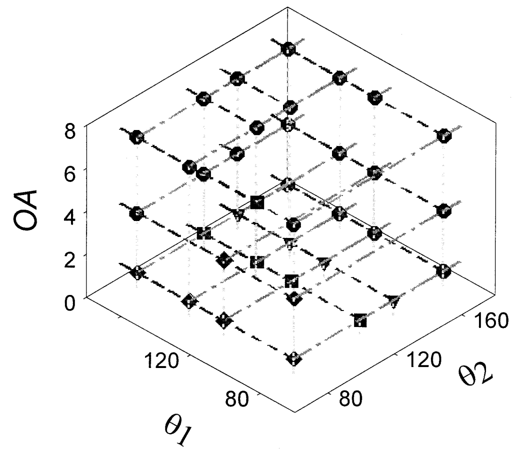

Fig. 4. This 3-dimension map represents the set of 38 fuzzy rules that are used by the FLD in our proposed measurement system, where ●, ▼, ■ and ♦ represent the defuzzification outputs 1, 0.7, 0.4, and 0, respectively.

where the inputs are $u_0 =$ OA, $\nu_0 = \theta_1$ and $y_0 = \theta_2$, the output is $w_0 = w$, and r is the number of fired rules. The technique of "center of gravity" is used to process the defuzzification and to calculate the numerical output w of the FLD, as expressed in (3)

$$w = \frac{\sum_{j=1}^{m} \mu_W(z_j) z_j}{\sum_{j=1}^{m} \mu_W(z_j)} \tag{3}$$

where m is the number of quantization levels of the output, z_j is the amount of output degree at the quantization level j, and $\mu_W(z_j)$ represents the membership value in the output fuzzy set W, which is a singleton.

B. RWRA

In Section II-A, (3) determines the truthfulness degree of OA of each heart beat, and the relationship between the cuff pressure and OA has been formulated as a static nonlinear mapping in the previous investigations [20]. Here, after each OA is given a weighting factor, w, representing the degree of truthfulness of the OA, by the FLD designed in Section II-A, the RWRA will be adopted to fit the envelope of the OAs in this subection. Because the normal OA pattern is close to a triangular shape [see, for example, Fig. 5(a)], the Lorentzian function is used to fit the envelope of OAs here. The Lorentzian function is defined as below

$$f(x) = \frac{1}{x^n + a_1 x^{n-1} + \cdots + a_{n-1} x + a_n} \tag{4}$$

where n is the model order, and a_is are the Lorentzian coefficients. Since the above Lorentzian function cannot be used by the linear regression method directly to reconstruct the oscillometric model, it is expanded to a power series as

$$f(x) \approx b_0 + b_1 x^{-1} + \cdots + b_m x^{-m} \tag{5}$$

where m is the model order, and b_is are the coefficients to be estimated. Our goal is made the output of the oscillometric model, $f(x)$, equal to OA when the input, x, is the corresponding cuff pressure, P_c.

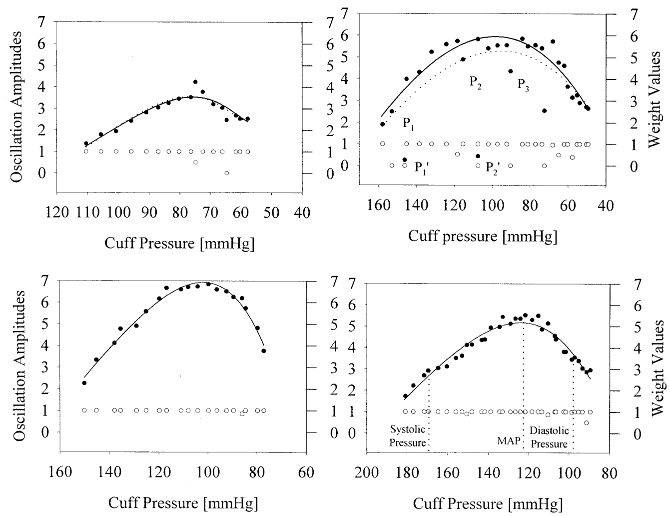

Fig. 5. Comparisons between the two envelopes of OAs generated by the RWRA (solid curve) and the TCFA (dotted curve). The solid circles denote the original OAs, and the open circles the weighting factor values decided by the proposed FLD. (a) A typical OA distribution from a subject without cardiovascular disease. (b) A typical OA distribution from a subject with arrhythmia, where P_1, P_2 and P_3 are the uncorrected peaks. (c) A typical OA distribution from a subject with atherosclerosis. (d) A typical OA distribution from a subject with hypertension. In Fig. (d), we also illustrate the way of determining the systolic/diastolic pressures (166/98 mmHg) from the solid fitted curve.

According to the expanded Lorentzian function in (5), in the linear regression function, the regression vector, ϕ, and the parameter vector, ξ, are defined below [21]

$$\phi^T(k) = [P_c^{-1}(k) \quad P_c^{-2}(k) \quad \cdots \quad P_c^{-m}(k)] \tag{6}$$

$$\xi^T = [b_0 \quad b_1 \quad \cdots \quad b_m] \tag{7}$$

where m is the model order and k is the sampled number. Therefore, the linear regression model can be expressed as

$$\mathrm{OA}(k) = \phi^T(k)\xi + \varepsilon(k) \tag{8}$$

where ε is the residual error and $\mathrm{OA}(k)$ is the oscillation amplitude corresponding to the cuff pressure at sample k, $P_c(k)$. For each data segment, the parameter vector of the model is determined using a weighted least-squares method. Let $\overline{\xi}$ denote an arbitrary estimate of the parameter vector ξ. Then, the loss function can be defined as

$$V(\overline{\xi}) = \tfrac{1}{2} \sum_{k=1}^{N} w(k)(\mathrm{OA}(k) - \phi^T(k)\xi)^2 \tag{9}$$

where N is the total beat (i.e., OA) number in the deflating process, and $w(k)$ is the weight (weighting factor) of $\mathrm{OA}(k)$ obtained by the FLD designed in Section II-B. An optimal estimate $\hat{\xi}$ of the parameter vector ξ can be determined from the measurement data, and $\{\mathrm{OA}(k)\}_{k=1}^{N}$ and $\{\phi(k)\}_{k=1}^{N}$ can be obtained by minimizing the loss function $V(\overline{\xi})$

$$\hat{\xi} = \left(\sum_{k=1}^{N} \phi(k)w(k)\phi^T(k)\right)^{-1} \sum_{t=1}^{N} \phi(k)w(k)\mathrm{OA}(k). \tag{10}$$

In (10), if we define $P_N = (\sum_{k=1}^{N} \phi(k)w(k)\phi^T(k))^{-1}$, then the RWRA to obtain (10) can be expressed by

$$\begin{aligned} P(k) = P(k-1) &- w(k)P(k-1)\phi(k) \\ &\cdot (I + \phi^T(k)w(k)P(k-1)\phi(k))^{-1}\phi^T(k)P(k-1) \end{aligned} \tag{11}$$

and

$$\begin{aligned} \hat{\xi}(k) = \hat{\xi}(k-1) &- w(k)P(k)\phi(k)(y(k) \\ &- \phi^T(k)\hat{\xi}(k-1)). \end{aligned} \tag{12}$$

Equations (11) and (12) are calculated for each measured OA, and the final $\xi(N)$ is the optimal parameter vector $\hat{\xi} = [\hat{b}_0, \hat{b}_1, \ldots, \hat{b}_m]$, where N is the total beat (i.e., OA) number. Putting the optimal $\hat{b}_i$s values into the expanded Lorentzian function in (5), we obtain the model describing the shape of change in OA over cuff pressure

$$f(x) \approx \hat{b}_0 + \hat{b}_1 x^{-1} + \cdots + \hat{b}_m x^{-m} \tag{13}$$

where x is the cuff pressure, P_c. That is, for a given measured cuff pressure P_c, (13) can estimate a reliable OA value; which is equal to

$$\mathrm{OA}(P_c) = f(P_c) \approx \hat{b}_0 + \hat{b}_1 P_c^{-1} + \cdots + \hat{b}_m P_c^{-m}. \tag{14}$$

The complexity and accuracy of the above computations depend on the model order. In the proposed algorithm, the Lorentzian function belongs to an irrational function. Normally, a lower-order model cannot characterize the actual nonlinear curve accurately. However, a high order model will result in high computation complexity in building the relationship between the cuff pressure (P_c) and OAs. Moreover, it will be easy to make a model divergent. Therefore, in subjective criteria, the model's order is chosen under the consideration that the model estimating the shape of change in OA over cuff pressure will not diverge. In objective criteria, the goal is to develop a model which increases the accuracy and robustness in the blood pressure measurement. Thus, we had tried the use of models with different orders and found that the resulting model by fitting the original envelope of the OAs can detect the most accurate systolic and diastolic pressures when n is equal to 4.

Using (11) and (12), the curve describing the shape of change in OA over cuff pressure can be reconstructed. With the reliable OA versus P_c model obtained in (13), which decides a curve on the OA-P_c plane, the systolic and diastolic pressures can be detected on this curve using the oscillometric method. As illustrated in Fig. 5(d), the cuff pressure corresponding to the maximum reconstructed OA represents the MAP. Then, according to proper systolic and diastolic ratios of the maximum reconstructed OA, the systolic and diastolic pressures are found from the corresponding cuff pressures, respectively. The systolic ratio and diastolic ratio used in our system are 0.55 and 0.7, respectively, which are decided experimentally as described in Section III.

III. Experimental Results

A. Experimental Procedure

The experimental protocol recruited 47 subjects (34 men and 13 women) with a mean age and $\pm$ standard deviation (SD) (61 $\pm$ 15) from 13 to 87 years, undergoing diagnostic evaluation for cardiovascular function or physical condition at the Hsinchu Hospital, Taiwan. ABP measurements in all subjects were performed with auscultation, and their systolic pressures ranged from 92 to 186 mmHg (132 $\pm$ 23) and diastolic pressures from 52 to 112 mmHg (77 $\pm$ 11). In the 47 subjects, 38 subjects with cardiovascular abnormalities, such as hypertension, atherosclerosis or arrhythmia, were included in the experimental group, and their systolic pressures ranged from 92 to 186 mmHg (137 $\pm$ 23) and diastolic pressures from 52 to 112 mmHg (79 $\pm$ 12). The other nine subjects (seven men and two women) without cardiovascular diseases, aging from 21 to 63 years (48 $\pm$ 13), were classified as the control group, and their systolic pressures ranged from 96 to 146 mmHg (113 $\pm$ 17) and diastolic pressures from 60 to 86 mmHg (71 $\pm$ 9).

In order to determine the proper systolic ratio and diastolic ratio as mentioned at the end of Section II, a noninvasive blood pressure analyzer (DNI NEVADA, CuffLink, Carson City, NV) was used to calibrate the proposed oscillometric measurement system. This analyzer can generate the simulated oscillation signals in the real cuff pressure measurement for a specified blood pressure. In our calibration, we set the blood pressure in the analyzer as the systolic pressure being 120 mmHg, the diastolic pressure being 80 mmHg, and MAP being 90 mmHg. The measured oscillation signal from the analyzer was then sent into our oscillometric measurement system, which then produced a OA-P_c curve describing the shape of change in OA over cuff pressure [see, for example, Fig. 5(d)]. The peak OA value ($\mathrm{OA}_{\mathrm{peak}}$) on the OA-$P_c$ curve was detected, and its corresponding cuff pressure was the MAP value. We first calibrated the pressure sensor in our oscillometric measurement system such that the detected MAP value was exact 90 mmHg. Then, we detected the OA values corresponding to the cuff pressure of 120 mmHg and 80 mmHg on the OA-P_c curve, denoted by $\mathrm{OA}_{\mathrm{systolic}}$ and $\mathrm{OA}_{\mathrm{diastolic}}$, respectively. Finally, the systolic ratio and diastolic ratio was set as $\mathrm{OA}_{\mathrm{systolic}}/\mathrm{OA}_{\mathrm{peak}}$ and $\mathrm{OA}_{\mathrm{diastolic}}/\mathrm{OA}_{peak}$, respectively. Such calibration was performed for several times and the obtained average systolic ratio and diastolic ratio are 0.55 and 0.7, respectively, in our experiments.

Noninvasive blood pressure measurements in the study were performed in two phases. In the first phase, the systolic and diastolic pressures in all subjects were measured with a mercury column sphygmomanometer by qualified nurses at the Hsinchu Hospital. In the second phase, the designed measurement system was used to record the brachial arterial pressure pulses. In the beginning, a cuff was placed around the subject's upper arm, and the cuff pressure was inflated up to 50 mmHg above the subject's systolic pressure. Then, the release valve was opened to decrease the cuff pressure at a deflation rate of 3 mmHg/s until the cuff pressure reached at 20 mmHg below the subject's diastolic pressure. The measured cuff pressure signals are then processed by the proposed oscillometric measurement system mentioned in Section II to obtain the systolic and diastolic pressures of the testing subject.

B. Statistical Analysis

Fig. 5 shows the OAs extracted from the recordings in Fig. 3. In Fig. 3(b), there are three uncorrected peaks, P_1, P_2 and P_3, that can be extracted by the proposed algorithm and shown in Fig. 5(b). For the subject with normal cardiovascular function, the envelope of the OAs generated by the RWRA is similar to that by the traditional curve fitting algorithm (TCFA), as shown in Fig. 5(a). In contrast, for the subject with cardiac arrhythmia, the envelope of the OAs produced by the RWRA is reasonably different from that by the TCFA, as shown in Fig. 5(b). Also, it is worthwhile noting that lower values of the weighting factors correspond to those OAs induced by the arrhythmic heart beats or the uncorrected peaks.

To assess the feasibility of the RWRA as well as the TCFA, a series of ABP measurements were carried out by the standard auditory detection procedure, and by the oscillometry combined with either one of RWRA and TCFA approaches. Table I lists the values of systolic, diastolic, pulse, and pooled (including systolic and diastolic) blood pressures determined by these two different approaches. Here, 47 subjects were enrolled in the blood pressure measurement. In the TCFA method, only 46 subjects' pressures were recorded due to one subject having a large amount of disturbance. Thus, there are 46 subjects' blood pressures are shown and statistically analyzed in Table I. The difference between the systolic blood pressures measured with the auscultation, and that with the oscillometry combined with the RWRA was found to be 4.7 mmHg, less than that with the oscillometry combined with the TCFA. In addition, the linear regression correlation coefficients (r) is used to describe the correlation between the auscultatory method and the oscillometry combined with the RWRA. If the r value is near 1, it indicates the linear function being a good description. For the systolic and diastolic blood pressure measurements using the auscultatory method or the oscillometry combined with the RWRA, the r values were found to be 0.98 and 0.91, respectively. Furthermore, in order to observe the measurement variability over a broad pressure range by the oscillometry combined with the RWRA, a linear regression analysis for the pooled measurements was performed, as shown in Fig. 6. The linear regression correlation coefficient between the auscultation and the oscillometry combined with the RWRA was found to be 0.99.

We also used the "t-test" to compare the accuracy of RWRA and TCFA in detecting the systolic and diastolic pressures and the results are also listed in Table I [22]. The t-test was performed by using the SigmaPlot mathematical analysis software (SPSS Inc., Chicago, IL). For a paired t-test on data sets $\{x_1, x_2, \ldots, x_n\}$ and $\{y_1, y_2, \ldots, y_n\}$, the t statistic is defined as by

$$t = \frac{\overline{D}}{S_{\overline{D}}} \tag{15}$$

TABLE I
SUMMARY OF THE BLOOD PRESSURE (BP) MEASUREMENTS BY THE AM, AND THE OSCILLOMETRY IN COMBINATION WITH THE TCFA, OR WITH THE PROPOSED RWRA, WHERE SEE = STANDARD ERROR OF ESTIMATE; r = CORRELATION COEFFICIENT; t IS THE t-TEST VALUE; p INDICATES THE PROBABILITY OF TWO MEANS BEING THE SAME

BP [mmHg]	AM (n = 46)	TCFA (n = 46)	RWRA (n = 46)	SEE (AM vs. TCFA)	SEE (AM vs. RWRA)	r (AM vs. TCFA	r (AM vs. RWRA)	t (p) (AM vs. TCFA)	t (p) (AM vs. RWRA)
Systolic Pressure	133 ± 23	134 ± 21	134 ± 22	4.9	4.7	0.97	0.98	-1.07 (0.29)	-1.17 (0.25)
Diastolic Pressure	78 ± 11	77 ± 11	77 ± 11	4.5	4.7	0.92	0.91	1.18 (0.24)	0.99 (0.33)
Pulse Pressure	56 ± 17	57 ± 16	57 ± 17	5.7	6.1	0.94	0.94	-1.88 (0.07)	-1.74 (0.09)
Pooled Pressure				5.1	4.9	0.99	0.99		

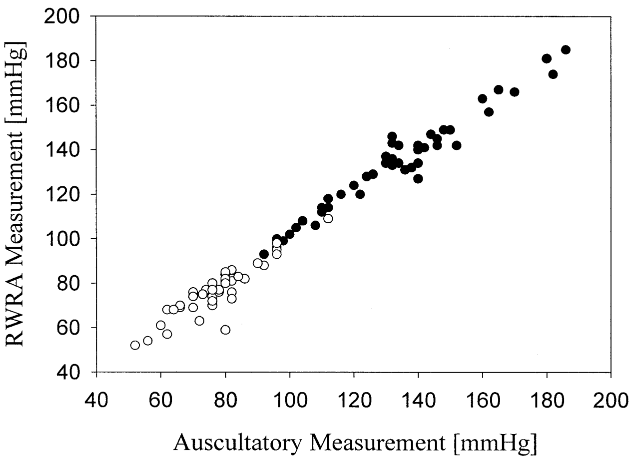

Fig. 6. Scatter plot of systolic (solid circles) and diastolic (open circles) pressures measured by the auscultatory detection, and the oscillometry combined with the RWRA. Study sample, $n = 47$; linear regression correlation, $r = 0.99$ ($p < 0.0001$); SEE = 4.9 mmHg; least-square fit line, $y = 0.56 + 0.996x$; $t = -0.02$ ($p = 0.98$).

where

$$\overline{D} = \frac{\sum_{i=1}^{n}(x_i - y_i)}{n} = \frac{\sum_{i=1}^{n} x_i}{n} - \frac{\sum_{i=1}^{n} y_i}{n} = \overline{x} - \overline{y} \quad (16)$$

$$S_{\overline{D}} = \sqrt{\frac{\sum_{i=1}^{n} D_i^2 - \frac{\left(\sum_{i=1}^{n} D_i\right)^2}{n}}{n(n-1)}} \quad (17)$$

where $\overline{x}$ is the mean of x values, $\overline{y}$ is the mean of y values, and $D_i = x_i - y_i$. Here, a P-value of < 0.05 was accepted as significant. In Table I, the p value indicates the probability of incorrectness in stating that the two means are different. Hence, the larger the p value is, the more similar the two data groups are. In order to test the performances between TCFA and RWRA in each individual case, Table II is used to describe the distribution of D_i for two groups' scores of TCFA to auscultatory method (AM) and RWRA to AM, respectively.

IV. DISCUSSIONS AND CONCLUSION

Previous studies, based on the oscillometric technique, have produced several skills to improve the accuracy of ABP measurement, such as adopting the Kalman filter to estimate the correct OAs [8], [9], using a step-decrease in cuff pressure to match the successive complex OAs at each pressure level [4], applying the Korotkoff sound to increase the signal to noise ratio [6], and differentiating the signal's slopes to predict the OAs [5]. In this paper, also based on the oscillometric technique, we proposed a new fuzzy-logic-based RWRA scheme to accurately measure the ABP by declining the interference in the OAs.

The proposed RWRA for fitting the envelop of OAs solves the two major disadvantages of a normal (unweighted) regression method (such as TCFA) using a polynomial function. The first disadvantage is due to the monotonous smoothness of the polynomial function. Because most of the normal OA patterns resemble a triangle shape, the polynomial function cannot catch up with an abrupt change in the OAs. Therefore, we applied, in this study, the Lorentzian function to fit the pattern of OAs of the cuff pressure. To become a real-time recursive algorithm, the Lorentzian function was expanded and represented by a linear function, as expressed by (5)–(8). Table III shows the comparison between the weighted mean square errors (MSEs) yielded by the RWRA with the polynomial function and those by the RWRA with the Lorentzian function, respectively. For the nine subjects with normal cardiovascular function, the MSEs generated with the Lorentzian function are always smaller than those with the polynomial function. The second disadvantage is that the TCFA is processed macroscopically. Thus, once certain parts of the OAs are contaminated by a large amount of noise, the TCFA approach will fail to provide a fit-well curve. As shown in Fig. 7, with two OAs greatly affected by artificial noise, the profile corresponding to those OAs obtained by the TCFA does not fit the OAs well. On the contrary, the profile provided by the RWRA matches quite well with those OAs. The reason for this is that the proposed RWRA excludes the two intentionally altered OAs in the reconstruction process. Noticeably, the values of the weighting factors for the two OAs are set to nearly zero according to the designed fuzzy logic rule in the proposed FLD. It is noticed that the Lorentzian function in its form of (5) was used both in the RWRA and the TCFA approaches in the comparisons made in Fig. 7.

We have made the comparisons of measurement accuracy between the blood pressures measured by the standard auscultatory detection procedure, and those by the oscillometric technique incorporating the algorithm of RWRA or TCFA.

TABLE II
COMPARISONS OF THE DIFFERENCES IN EACH INDIVIDUAL CASE GENERATED BY THE TCFA AND RWRA METHODS FOR SYSTOLIC AND DIASTOLIC PRESSURES, RESPECTIVELY

Pressure Difference (mmHg)			0	1	2	3	4	5	6	7	> 7
People Number	AM vs. TCFA	Systolic Pressure	4	8	7	6	5	6	4	1	6
		Diastolic Pressure	2	11	10	4	12	2	2	0	3
	AM vs. RWRA	Systolic Pressure	4	8	8	4	12	2	3	1	6
		Diastolic Pressure	4	12	8	4	10	2	4	0	3

TABLE III
COMPARISON OF THE WEIGHTED MSEs GENERATED BY THE RWRA WITH POLYNOMIAL FUNCTION AND THOSE WITH LORENTZIAN FUNCTION, RESPECTIVELY, IN NINE SUBJECTS WITHOUT CARDIOVASCULAR DISEASES

Subject	1	2	3	4	5	6	7	8	9
Lorentzian function	0.043	0.028	0.020	0.020	0.034	0.031	0.032	0.052	0.058
Polynomial function	0.045	0.042	0.028	0.031	0.036	0.044	0.038	0.062	0.068

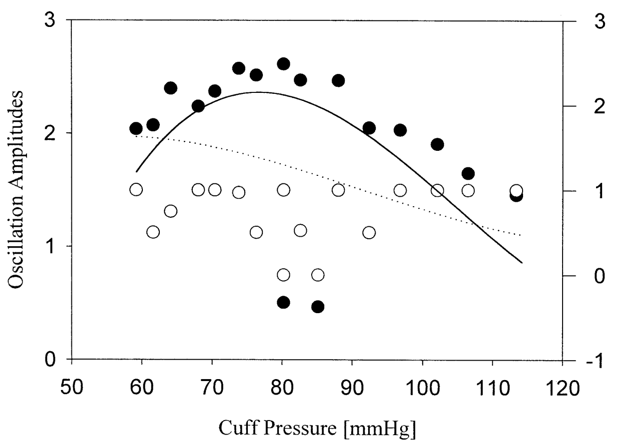

Fig. 7. Two OA profiles obtained with the TCFA (dotted curve) and the proposed RWRA (solid curve), respectively. The solid circles denote the original OAs, and the open circles the weighting factor values. Note that the dotted curve does not fit well with the original OAs, but the solid curve does.

According to the previous investigation [10], the correlation coefficient between two data groups can be used to indicate the similarity degree of these two data groups. Based on this index, it is demonstrated, in the systolic pressure measurements, that there is a high correlation coefficient ($r = 0.98$, SEE = 4.7 mmHg, and $n = 46$) between the measured results of the auscultatory technique and those of the oscillometry combined with the proposed RWRA algorithm, whereas there is a lower correlation coefficient ($r = 0.97$, SEE = 4.9 mmHg, and $n = 46$) between the measured results of the auscultatory technique and those of the oscillometry combined with the conventional TCFA (Table I). Similarly, in the results of t-test, the determined systolic pressure of RWRA ($t = -1.17, p = 0.25$) is more accurate than that of TCFA ($t = -1.07, p = 0.29$). The determined diastolic pressure of RWRA ($t = 0.99$, $p = 0.33$) is slightly less accurate than that of TCFA ($t = 1.18$, $p = 0.24$). But in the pooled pressure measurements, the RWRA displays better accuracy ($r = 0.99$, SEE = 4.9 mmHg) than the TCFA ($r = 0.99$, SEE = 5.1 mmHg), when compared with the auscultatory technique. Therefore, we would like to reemphasize that one (out of 47) subject's pressure records contained a large amount of disturbance, and was excluded in the above analysis.

In conclusion, the proposed RWRA is quite robust in rejecting external interference induced by either artificial motion or arrhythmic disturbance and in reconstructing the relationship between the cuff pressure and OA. Form this reconstructed relationship, the accurate systolic and diastolic pressures can be detected. The contributions of this paper are summarized as follows.

1) The proposed RWRA-based modeling (or "curve fitting") technique is aimed at the processing of the oscillation waveforms produced by the oscillometric blood pressure measurement. Hence, the characteristics of such signals are fully utilized in our algorithm, such as the use of Lorentzian function to fit the OA patterns due to their similarity, the use of the technique of maximum change of positive slope for peak detection due to the reflective notch waveform appearing in a raw blood pressure waveform, and the extraction of disturbance features (θ_1 and θ_2 in Fig. 3) of the OA patterns for fuzzy estimates of reliability by observing various types of oscillation waveforms corresponding to the normal subject and the subjects with arrhythmia, atherosclerosis, and hypertension, etc.
2) In the proposed RWRA, an FLD is established to detect the irregularities within the succession of peaks on the oscillation waveforms. Fuzzy estimates of reliability were then used as weights in a recursive regression analysis to extract the shape of change in OA over cuff pressure. The FLD effectively reduced the effect of artifacts caused by cardiovascular diseases or measurement motion disturbance and determined the truthfulness of the oscillation pulse. The fuzzy logic rules were obtained by observing various types

of oscillation waveforms corresponding to the subjects with normal or abnormal cardiovascular functions. Hence, unlike normal general-purpose smoothing methods, the proposed FLD embeds the expert knowledge of ABP into its structure and reasoning process.

3) Extensive clinical tests were done to verify the performance of the proposed method. The results of the proposed method were compared in 46 subjects to blood pressure measurements obtained by conventional auscultatory procedure of measurement. The study nicely showed that artifacts were reduced and there was a good correlation between both methods.

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