Analysis on the accuracy of a decision support system for hypertension monitoring

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***Abstract*— In this paper, we propose a novel method to estimate the accuracy of a decision support system for hypertension monitoring. The decision support system is designed building on a diagnosis standard in medicine, and one decision made by this system depends on both the blood pressure data gathered by medical sensors and some contexts that are manually entered by clinicians. When analyzing the system accuracy, we take into account both the potential sensors' errors and the errors of entering context. In addition, we propose a novel method for the estimation of system accuracy; this method is motivated by the fact that the traditional method to estimate system accuracy would overestimate the system accuracy (the details would be presented in Section III.C.). Finally, we compare the system accuracy estimated by the proposed method and that estimated by the traditional method. Our study shows that our proposed method can well estimate the system accuracy.**

***Index Terms*— Wireless heath, hypertension monitoring, decision support system, system accuracy.**

I. Introduction

According to the WHO's annual report, hypertension causes 13% of the total deaths all over the world [1]. At the same time, hypertension is also a 'silent killer' since it could lead to complications, such as heart attacks, strokes, and kidney failures without any symptoms [1]. To reduce the risk of complications, people should check their blood pressure at regular intervals. However, those living far away from a hospital or being busy with their work dislike personally go to a hospital to check their blood pressure. Motivated by solving this problem, we attempt to design a decision support system for hypertension monitoring. This system could automatically collect patient's data and make some decisions on the status of a hypertension patient. Once some emergent cases occur, some messages on patient status and related medical data would be sent to some clinicians or doctors via advanced telecommunication and internet technologies. In this case, patients can stay at home or at office to get regular checks of their blood pressure.

In our decision support system, a decision on patient status is made by referring to a diagnosis standard of China [2], and the process of designing this system can be in parallel transplanted into the cases of referring to hypertension diagnosis standards of other countries. To the best of our knowledge, no study has been done to design a decision support unit for hypertension diagnosis (The decision support unit proposed in [3] concerns no hypertension diagnosis but the suitable time for a patient to measure blood pressure).

Additionally, we attempt to prove that our system can offer reliable decisions, since no one would trust a system if it cannot make decisions with acceptable accuracy. In our system, making a decision depends on both the blood pressure data gathered by medical sensors and some contexts manually entered by clinicians. To estimate the system accuracy, we take into account both the sensors' errors as well as the errors caused by the manual entry of contexts. Based on these types of errors, we would overestimate the system accuracy if we using the traditional method, which only concentrates on the final result of decisions but cannot differentiate whether this decision is made in a correct context (This problem would be detailed in Section III.C.). Thus, we propose a novel method to estimate the system accuracy. Our study shows that in comparison with the traditional method, our proposed method can better estimate the system accuracy.

II. Architecture of our hypertension monitoring system

Our decision support system (We call it WeHealth system) for hypertension monitoring is designed to make decisions on the status of patients and deliver hypertension-related services and information via telecommunications and computing technologies. In our WeHealth system, blood Pressure (BP) data of a particular patient are gathered by a BP measurement device and then transferred to a data server in hospital via wireless networks and internet. Building on these arriving BP data, a decision support unit in the data server would make some initial decisions on patient condition. By referring to these initial decisions, doctors would make the final decisions on patient condition and send their diagnosis to patients through a reverse link, denoted as *diagnosis feedback* in Fig.1.

In our system, a decision on patient status is made based on a standard in medicine for the risk stratification of hypertension [4], shown in Table I. In Table I, stage 1, stage 2 and stage 3 represent different types of hypertension, and this classification is based on the values of systolic pressure and diastolic pressure, shown in Table II. The risk factors, target organ damage and complications related to the risk stratification of hypertension are also presented in [4].

Based on this standard in medicine, the flow chart of our decision support system is shown in Fig.2. As illustrated in Fig.2, the working process of our system is composed of two

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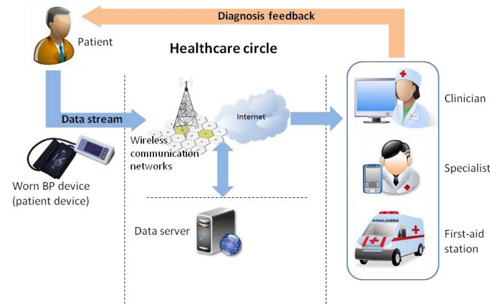


Fig. 1. Architecture of the decision support system for hypertension monitoring.

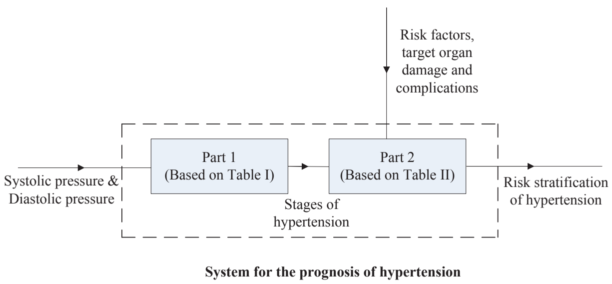


Fig. 2. Flow chart of the decision support system for hypertension monitoring.

parts, and the first part (part 1) and the second part (part 2) correspond to Table II and Table I, respectively. In part 1, its inputs include systolic pressure and diastolic pressure, and its output is the stage of hypertension, which is also one input of part 2. The other inputs of part 2 include the risk factors, target organ damage and complications, and the output of part 2 is the risk stratification of hypertension. Specifically, the risk stratification of hypertension includes four risk levels, namely, low risk, moderate risk, high risk and extremely high risk. These four risk levels are for the prognosis of cardiocerebral vascular diseases in the future 10 years. Low risk, moderate risk, high risk and extremely high risk represent that the risk of cardiocerebral vascular diseases for a particular patient in the future 10 years is smaller than 15%, $15\% - 20\%$, $20\% - 30\%$ and larger than 30%, respectively.

III. Accuracy analysis of our monitoring system

In this section, we will analyze the accuracy of our hypertension monitoring system. Firstly, we clarify the assumptions to analyze the accuracy. Then, we analyze the accuracy of our monitoring system by the traditional accuracy estimation method. Finally, we point out the potential problems of this traditional accuracy estimation method in our application scenario and propose a novel accuracy estimation method by modifying the traditional method.

A. Assumptions for analysis on system accuracy

As shown in Fig.2, our system is composed of two groups of medical sensors: one group used to acquire systolic pressure and the other group used to acquire diastolic pressure. We denote the average sensing errors of group 1 and group 2 as e_1 and e_2, respectively. Then, we assume that e_1 is uniformly distributed in $[-e_{1max}, e_{1max}]$ and e_2 is uniformly distributed in $[-e_{2max}, e_{2max}]$, where e_{1max} and e_{2max} are the maximal sensing error of group 1 and group 2, respectively. Additionally, we assume that the values of both systolic pressure and diastolic pressure are normally distributed [3]. Specifically, if the value of systolic pressure is denoted by p_1, then the probability density function (pdf) of p_1 is

$$pdf_{p_1}(x) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} \tag{1}$$

where the mean and standard deviation (std) of p_1 are μ_1 and σ_1, respectively.

Similarly, given the mean μ_2 and std σ_2, the pdf of the value of diastolic pressure p_2 can be expressed as

$$pdf_{p_2}(x) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}} \tag{2}$$

Equations (1) and (2) show the distribution of exact systolic pressure and that of exact diastolic pressure, respectively. The measured value of systolic pressure, denoted as pa_1, equals the summation of the exact value p_1 and e_1. And the measured value of diastolic pressure, denoted as pa_2, equals the summation of the exact value p_2 and e_2. Assuming that p_1 and e_1 are independent, the distribution of pa_1 can be expressed as

$$pdf_{pa_1}(x) = pdf_{p_1}(x) * pdf_{e_1}(x) \tag{3}$$

where $A * B$ represents that A is convolved with B, given

$$pdf_{e_1}(x) = \begin{cases} 1/(2e_{1\max}) & if\ x \in [-e_{1\max}, e_{1\max}] \\ 0 & otherwise \end{cases} \tag{4}$$

Similarly, assuming that p_2 and e_2 are independent, the distribution of pa_2 can be expressed as

$$pdf_{pa_2}(x) = pdf_{p_2}(x) * pdf_{e_2}(x) \tag{5}$$

where $A * B$ represents that A is convolved with B, given

$$pdf_{e_2}(x) = \begin{cases} 1/(2e_{2\max}) & if\ x \in [-e_{2\max}, e_{2\max}] \\ 0 & otherwise \end{cases} \tag{6}$$

For simplicity, we use stage 0 to denote the case of *normal or prehypertension* in Table II. As shown in Table II, hypertension is classified into four stages, determined by both systolic pressure and diastolic pressure. If p_1 and p_2 fall into the ranges corresponding to the same stage, then, the hypertension can be simply classified into this stage. For example, when $p_1 = 130$ and $p_2 = 80$, the hypertension is classified into stage 0. If p_1 and p_2 fall into the ranges corresponding to two different stages, then, the hypertension is classified into the higher one of these two stages. For instance, when $p_1 = 150$ and $p_2 = 80$, then, the hypertension is classified into stage 1.

To evaluate the accuracy of our system, we define some probabilities based on four stages of hypertension. The first group of probabilities are the probability of correct decisions on the patient status, which are the the joint probabilities of

	Risk factors and history of hypertension	Blood pressure		
		Stage 1	Stage 2	Stage 3
case 1	No risk factors	Low risk	Moderate risk	High risk
case 2	One or two risk factors	Moderate risk	Moderate risk	Extremely high risk
case 3	More than three risk factors or diabetes or target organ damage	High risk	High risk	Extremely high risk
case 4	Complications	Extremely high risk	Extremely high risk	Extremely high risk

TABLE I

STANDARD FOR THE RISK STRATIFICATION OF HYPERTENSION [4]

Classification	Systolic pressure (mmHg)	Diastolic pressure (mmHg)
Normal or Prehypertension	< 139	< 89
Hypertension (Stage 1)	140-159	90-99
Hypertension (Stage 2)	160-179	100-109
Hypertension (Stage 3)	> 179	> 109

TABLE II

CLASSIFICATION OF HYPERTENSION [4]

the correct decision and the truth. We define T_0, T_1, T_2 and T_3 as

$$T_i = pr(Decision\ \ in\ \ stage\ i, actual\ \ stage\ i) \quad (i = 0, 1, 2, 3) \tag{7}$$

Then, we describe the false probabilities as the joint probabilities of the incorrect decision and the truth. We define FP_{10}, FP_{20}, FP_{30}, FP_{21}, FP_{31}, FP_{32}, FN_{10}, FN_{20}, FN_{30}, FN_{21}, FN_{31}, FN_{32} as

$$\begin{aligned} FP_{ij} &= pr(Decision\ \ in\ \ stage\ i, actual\ \ stage\ j) \\ FN_{ij} &= pr(Decision\ \ in\ \ stage\ j, actual\ \ stage\ i) \\ & \qquad (i, j = 0, 1, 2, 3, i > j) \end{aligned} \tag{8}$$

In Table II, both systolic pressure and diastolic pressure have three thresholds to classify four stages of hypertension. We denote the thresholds for systolic pressure as $L_{11}(L_{11} = 139)$, $L_{12}(L_{12} = 159)$, and $L_{13}(L_{13} = 179)$. Additionally, we denote the thresholds for diastolic pressure as $L_{21}(L_{21} = 89)$, $L_{22}(L_{22} = 99)$, and $L_{23}(L_{23} = 109)$. Assuming that the maximal sensing errors e_{1max} and e_{2max} are far less than $L_{12} - L_{11}$, $L_{13} - L_{12}$, $L_{22} - L_{21}$, $L_{23} - L_{22}$, then, we have

$$\begin{aligned} & FP_{ij} = 0\ \ and\ \ FN_{ij} = 0 \\ & when\ \ i - j > 1\ \ (i, j = 0, 1, 2, 3) \end{aligned} \tag{9}$$

B. Analysis on system accuracy by the traditional accuracy estimation method

As shown in Fig.2, the output of our hypertension monitoring system is stratification of hypertension risks. It is determined by the blood pressure (systolic pressure and diastolic pressure) as well as the contexts (e.g. risk factors, target organ damage and complications), which are manually entered by healthcare staff. Thus, the errors of system output result from both the errors in blood pressure measurement by medical sensors and the errors of contexts entry. As shown in Table I, we use case 1, case 2, case 3, case 4 to represent *no risk factors*, *One or two risk factors*, *More than three risk factors or diabetes or target organ damage*, and *Complications*, respectively. For simplicity, we use *N*, *L*, *M*, *H*, and *E* to represent the status of *Normal*, *Low risk*, *Moderate risk*, *High risk*, and *Extremely High risk*.

The system accuracy with the traditional accuracy estimation method can be expressed as [5]

$$\begin{aligned} ACC_T = &\ pr(Decision\ \ in\ \ N, Truth\ \ in\ \ N) \\ & + pr(Decision\ \ in\ \ L, Truth\ \ in\ \ L) \\ & + pr(Decision\ \ in\ \ M, Truth\ \ in\ \ M) \\ & + pr(Decision\ \ in\ \ H, Truth\ \ in\ \ H) \\ & + pr(Decision\ \ in\ \ E, Truth\ \ in\ \ E) \end{aligned} \tag{10}$$

Assuming that the risk factors are independent from the values of blood pressure, these probabilities in equation (10) can be expressed as equation (11), where we define $\hat{s}$ =‘decision in stage’, s =‘actual stage’, $\hat{c}$ =‘entered context’, c =‘real context’ (the same below in equation (12), equation (13), and equation (14)).

C. Analysis on system accuracy by the modified accuracy estimation method

In the traditional method, the estimation of system accuracy only depends on whether the decisions on patient status are correct. It cannot differentiate whether the decision is made in a correct context or in an incorrect context, since an incorrect entered context may also lead to a correct decision. For instance, when the medical data is in stage 1, both the exact context (we say case 1) and the entered context (we say case 2) can reach the same decision *M*. While the decision on patient status is correct, the system can provide little information to doctors and even mislead doctors if the decision is made in an incorrect context, since doctors may take different actions to the patient in different contexts [6]. Due to the limit of the traditional method, we propose a novel method to estimate system accuracy by modifying the traditional estimation method. In the proposed method, the evaluation of system accuracy depends on not only the decisions on patient status but the contexts in which these decisions are made.

$$
\begin{aligned}
&pr(Decision\ \ in\ \ N, Truth\ \ in\ \ N) = pr(\hat{s}=0,\ s=0)\\
&pr(Decision\ \ in\ \ L, Truth\ \ in\ \ L) = pr(\hat{s}=1,\ s=1,\ \hat{c}=1,\ c=1)\\
&pr(Decision\ \ in\ \ M, Truth\ \ in\ \ M) = \sum_{p,q\in\{1,2\}} pr(\hat{s}=2,\ s=2,\ \hat{c}=p,\ c=q) + \sum_{p\in\{1,2\}} pr(\hat{s}=2,\ s=1,\ \hat{c}=p,\ c=2)\\
&+ \sum_{p\in\{1,2\}} pr(\hat{s}=1,\ s=2,\ \hat{c}=2,\ c=p) + pr(\hat{s}=1,\ s=1,\ \hat{c}=2,\ c=2)\\
&pr(Decision\ \ in\ \ H, Truth\ \ in\ \ H) = pr(\hat{s}=3,\ s=3,\ \hat{c}=1,\ c=1) + \sum_{p,q\in\{1,2\}} pr(\hat{s}=p,\ s=q,\ \hat{c}=3,\ c=3)\\
&+ \sum_{p\in\{1,2\}} pr(\hat{s}=3,\ s=p,\ \hat{c}=1,\ c=3) + \sum_{p\in\{1,2\}} pr(\hat{s}=p,\ s=3,\ \hat{c}=3,\ c=1)\\
&pr(Decision\ \ in\ \ E, Truth\ \ in\ \ E) = \sum_{p,q\in\{2,3\}} pr(\hat{s}=3,\ s=3,\ \hat{c}=p,\ c=q) + \sum_{p,q\in\{1,2,3\}} pr(\hat{s}=p,\ s=q,\ \hat{c}=4,\ c=4)\\
&+ \sum_{p\in\{1,2,3\}} pr(\hat{s}=3,\ s=p,\ \hat{c}=2,\ c=4) + \sum_{p\in\{1,2,3\}} pr(\hat{s}=p,\ s=3,\ \hat{c}=4,\ c=2)
\end{aligned}
\tag{11}
$$

Specifically, the system accuracy by the modified method can be expressed as equation (12).

$$
\begin{aligned}
ACC_M = {} & pr(Decision\ \ in\ \ N, Truth\ \ in\ \ N)\\
& + pr(Decision\ \ in\ \ L, Truth\ \ in\ \ L, \hat{c}=m, c=n)\\
& + pr(Decision\ \ in\ \ M, Truth\ \ in\ \ M, \hat{c}=m, c=n)\\
& + pr(Decision\ \ in\ \ H, Truth\ \ in\ \ H, \hat{c}=m, c=n)\\
& + pr(Decision\ \ in\ \ E, Truth\ \ in\ \ E, \hat{c}=m, c=n)\\
& (m,n\in\{1,2,3,4\}, m=n)
\end{aligned}
\tag{12}
$$

It is easy to show that the system accuracy estimated by the traditional method (ACC_T) is larger than that estimated by the modified method (ACC_M), since the equation (11) can be transformed into equation (13). In other words, the system accuracy is overestimated by the traditional method.

$$
\begin{aligned}
ACC_M = {} & pr(Decision\ \ in\ \ N, Truth\ \ in\ \ N)\\
& + pr(Decision\ \ in\ \ L, Truth\ \ in\ \ L, \hat{c}=m, c=n)\\
& + pr(Decision\ \ in\ \ M, Truth\ \ in\ \ M, \hat{c}=m, c=n)\\
& + pr(Decision\ \ in\ \ H, Truth\ \ in\ \ H, \hat{c}=m, c=n)\\
& + pr(Decision\ \ in\ \ E, Truth\ \ in\ \ E, \hat{c}=m, c=n)\\
& (m,n\in\{1,2,3,4\})
\end{aligned}
\tag{13}
$$

D. Further deduction of system accuracy

The probability $pr(\hat{s}=p,\ s=q,\ \hat{c}=m,\ c=n)$ can be calculated as

$$
\begin{aligned}
&pr(\hat{s}=p,\ s=q,\ \hat{c}=m,\ c=n) = pr(\hat{s}=p,\ s=q)\times\\
&pr(\hat{c}=m,\ c=n)\ \ (p,q\in\{0,1,2,3\},\ m,n\in\{1,2,3,4\})
\end{aligned}
\tag{14}
$$

given the assumption that the risk factors are independent from the values of blood pressure.

From equation (14), it is easy to find that both ACC_T and ACC_M are determined by T_i $(i=0,1,2,3)$, FN_{ij} $(i,j=0,1,2,3,\ i-j=1)$ and FP_{ij} $(i,j=0,1,2,3,\ i-j=1)$, given the joint probability of $pr(\hat{c}=m,\ c=n)$ $(m,n=1,2,3,4)$, which is determined by the statistical result in medicine. In the following, we calculate T_0, T_1, T_2, T_3, FP_{10}, FP_{21}, FP_{32}, FN_{10}, FN_{21}, FN_{32}, respectively.

The first group (T_0, T_1, T_2, T_3) as well as the second group (FP_{10}, FP_{21}, FP_{32}, FN_{10}, FN_{21}, FN_{32}) can be expressed as the combination of $pr(L_{i(j-1)} < p_i + e_i < L_{ij}, L_{ij} < p_i < L_{i(j+1)})$ $(L_{i0}=-\infty, L_{i4}=\infty; i=1,2; j=1,2,3)$, $pr(L_{i(j-1)} < p_i < L_{ij}, L_{ij} < p_i + e_i < L_{i(j+1)})$ $(L_{i0}=-\infty, L_{i4}=\infty; i=1,2; j=1,2,3)$, and $pr(L_{i(j-1)} < p_i < L_{ij}, L_{i(j-1)} < p_i + e_i < L_{ij})$ $(L_{i0}=-\infty, L_{i4}=\infty; i=1,2; j=1,2,3,4)$. These probabilities can be further deduced as

$$
\begin{aligned}
&pr(L_{i(j-1)} < p_i + e_i < L_{ij}, L_{ij} < p_i < L_{i(j+1)})\\
&= \tfrac{1}{4e_{imax}} \int_{-e_{imax}}^{0} \int_{L_{ij}}^{L_{ij}-y} pdf_{p_i}(x)dxdy\\
&pr(L_{i(j-1)} < p_i < L_{ij}, L_{ij} < p_i + e_i < L_{i(j+1)})\\
&= \tfrac{1}{4e_{imax}} \int_{0}^{e_{imax}} \int_{L_{ij}-y}^{L_{ij}} pdf_{p_i}(x)dxdy\\
&pr(L_{i(j-1)} < p_i < L_{ij}, L_{i(j-1)} < p_i + e_i < L_{ij})\\
&= \tfrac{1}{4e_{i\max}} \int_{0}^{e_{i\max}} \int_{L_{i(j-1)}}^{L_{ij}-y} pdf_{p_i}(x)dxdy +\\
&\quad \tfrac{1}{4e_{i\max}} \int_{-e_{i\max}}^{0} \int_{L_{i(j-1)}-y}^{L_{ij}} pdf_{p_i}(x)dxdy
\end{aligned}
\tag{15}
$$

By substituting equation (15) into the equation (11) and equation (12), we can calculate the system accuracy.

IV. Simulation and discussion

A. Verification of our assumptions by measurements

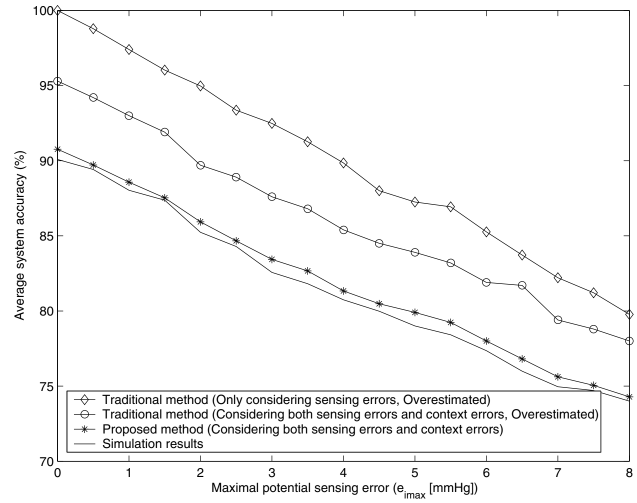
Our model for the analysis of system accuracy is based on three assumptions: (1) both the systolic pressure and diastolic pressure are distributed normally; (2) the difference between any two thresholds is larger than the maximal potential value of sensing errors; (3) the errors of sensors are uniformly distributed. Among these assumptions, the first two are shown to hold in reality in [2], and the third is verified in [7] by measuring the values of blood pressure. The experiment equipment for measurements is a T-shaped pipe fitted with two outlets. One outlet is connected to a mercury Sphygmomanometer, and the other is connected to an electronic blood-pressure sensor. With this pipe, we can get the values of blood pressure measured by both the sensor and the mercury Sphygmomanometer. We define sensing errors as the difference of these two values, since the values read from the mercury Sphygmomanometer are assumed to be the exact values. This experiment is repeated 500 times, and the result shows that the distribution of sensing errors is almost uniform.

B. Discussion on average system accuracy

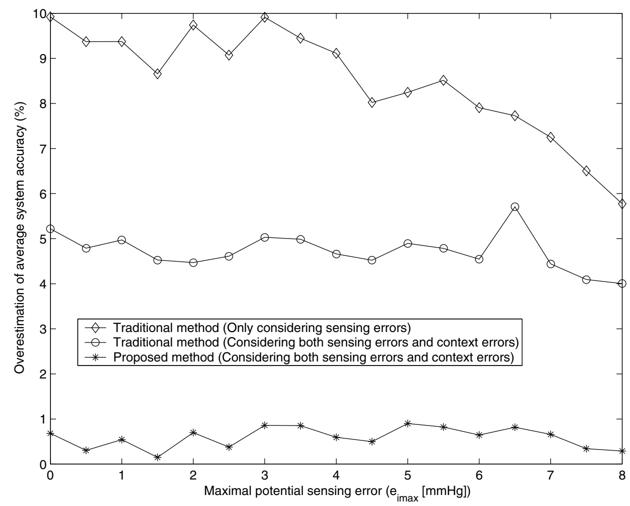
Building on the uniform distribution of sensing errors, we demonstrate the issue with respect to average system accuracy. In view of equation (12) and equation (13), we can numerically get the average system accuracy with both the traditional method and the proposed method. Additionally, setting the given probability $pr(\hat{c} = m|c = n) = 1$, we can attain the system accuracy considering only the errors of sensors.

On the other hand, we run Monte Carlo simulations to verify our numerical results. In the Monte Carlo simulation, we use Matlab to generate both the sensing errors and the error of entering contexts. Then, we simulate the measured blood pressure by adding up the value of exact blood pressure and that of sensing error; we simulate the entered context by referring to the given probability of $pr(\hat{c} = m|c = n)$. Next, we compare the decision made by the system using the exact blood pressure and the exact context as input with the decision made by the system using both the measured blood pressure and the entered context as input. Finally, we record the number of both correct and incorrect decisions after repeating the abovementioned process thousands of times. This accuracy is viewed as a benchmark for the estimated accuracy by various numerical methods.

Fig.3 shows that only considering one type of error would overestimate the system accuracy, and the overestimation is about 8% on average. In addition, viewing some decisions made in incorrect contexts as correct decisions, the traditional method considering both types of errors will also overestimate the system accuracy, and the overestimation always keeps around 5%. Fig.3 also shows that our proposed can well estimate the system accuracy (the difference is less than 1%).



(a) Average system accuracy VS. Maximal potential sensing errors.



(b) Overestimation of average system accuracy VS. Maximal potential sensing errors

Fig. 3. Average system accuracy using various estimation methods.

V. Conclusion

In this paper, building on a standard in medicine, we design a decision support system for hypertension monitoring. Additionally, we propose a theoretical method to evaluate the accuracy of our hypertension monitoring system by linking the system accuracy with the distribution of sensors' errors and the errors of context entry. To show the reliability of our method, we demonstrate the validity of all three assumptions of our method, either by citing reference or by taking measurement. To show the efficiency of our method, we compare the system accuracy estimated by our method and that by the traditional method. The result shows that our proposed method can well estimate the system accuracy. Our study can offer some reference for the designing a decision support system for hypertension monitoring and estimating its system accuracy.

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