A Health Status Evaluation Method for Chronic Disease Patients Based on Multivariate State Estimation Technique Using Wearable Physiological Signals: A Preliminary Study

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Abstract. Since chronic disease has become one of the most profound threats to human health, effective evaluation of human health and disease status is particularly important. In this study, we proposed a method based on Multivariate State Estimation Technique (MSET) by using physiological signals collected by a wearable device. Residual was defined as the difference between the actual value of each observed parameter and the estimated value obtained by MSET. The high-dimensional residual series were fused into a Multivariate Health Index (MHI) using a Gaussian mixture model. To preliminarily validate this method, we designed a retrospective observational study of 17 chronic patients with coronary artery disease combined high risk of heart failure whose Brain Natriuretic Peptide (BNP) had changed significantly during hospitalization. The results show that the distribution of residuals estimated by MSET had some regularity, in which the Pearson correlation coefficients between

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Cohen Standardized Mean Difference (SMD) and Overlapping Coefficient (OVL) of MHI and the change of BNP examination results reached 0.786 and 0.835, with their p-values less than 0.001, respectively. We preliminarily demonstrated that the model can reflect the level of change in human health status to some extent. This MSET-based approach shows great potential for applications of treatment effect evaluation, and provides abundant information from physiological signals in chronic disease management.

Keywords: Health status evaluation · Chronic disease management · Multivariate state estimation technique · Physiological signals

1 Introduction

Chronic disease has become one of the most profound threats to human health [18,27]. For example, a well-known chronic disease, Chronic Obstructive Pulmonary Disease (COPD), has become the third leading cause of death worldwide in the last decade [4]. Furthermore, according to a report in 2018, two-fifths of deaths in China are attributed to cardiovascular diseases (CVD), which affects about 290 million patients [18]. While chronic diseases have brought great medical burden, family burden and social burden across the world, this situation has gotten even worse since the COVID-19 pandemic. How to treat and manage chronic diseases has become an urgent problem that remains unsolved. For chronic disease management (CDM), effective evaluation of human health and disease status is particularly important.

Currently, the widely used clinical method to evaluate a patient's health and disease status still largely relies on lab test results [3]. It compares a patient's several key lab examination values with those values of the pre-defined reference ranges, which are obtained from a healthy population [7,10]. However, this evaluation method has three main shortcomings. First, the lab examination normal intervals formed by large-sample healthy people are not always appropriate for everyone when individualized medicine is considered [26,29]. Second, the lab examination-based evaluation method lacks timeliness to some extent, because many results need half or even more days to be available. Third, in general wards, the frequency of lab result collection is significantly lower than that of physiological signal collection. For example, a hospitalized patient in China hardly takes daily lab examination due to unnecessary over-collection and expensive out-of-pocket cost. Furthermore, the timing that a patient takes lab examination is mostly determined by a physician's experience, which aggravates the uncertainty of estimating the patient's condition.

In the era of the Internet of Things and Digital Medicine, wearable technology enables people to collect physiological signals continuously, enjoying the merits of easy accessibility, real-time acquisition, and high sampling rate. Physiological signals such as electrocardiogram (ECG), heart rate (HR), breathing rate (BR) contain rich medical information that has a great potential for disease early

warning, rehabilitation assessment and CDM [1,9,20]. Several research groups have proposed various methods to solve the problem of health status recognition based on physiological signals: Li-wei H. Lehman et al. conducted a series of studies that analyzed the dynamical behaviors in cardiovascular variables which can be used to recognize the state of a patient [12,13,15]. In [5], Principal Component Analysis and a Hidden Markov Model were adopted to recognize the abnormalities in physiological signals to realize health status recognition.

Due to the high complexity of human body, each individual has her/his specific physiological wave patterns. Most of the previous studies are based on large sample specific population, reflecting population characteristics while individual differences are largely eliminated in population analysis. Moreover, chronic disease patients are often elderly and suffered from multiple chronic diseases at the same time, entangling the analysis of their health status conditions. Furthermore, their individual differences pose a challenge for in-depth mining of physiological signals and research on state identification. Thus, how to establish a physiological-signal-based method to individually evaluate the health status of chronic disease patients is still a problem that needs investigation.

To resolve the above problems, the Multivariate State Estimation Technique (MSET) can be used, which is first proposed by Singer R M et al. at 1997 [23]. MSET measures the difference between the observed status of the system and historical status when the system running normally. This algorithm is often used to realize fault early warning of electron devices or equipment and has been successfully deployed in several industrial scenarios [16,28,33]. The advantages of MSET has been proved in fast training and accurate prediction. In medicine domain, R. Matthew Pipke et al. [21] used MSET to conduct individualized non-parametric modeling for patients with heart failure. They collected HR, BR, Pulse Transit Time (PTT), Pulse Pressure Index (PPI), blood oxygen saturation, etc. by a wearable device, and finally realized the effective identification of dynamic changes in these physiological signals of patients. Richard L. Summers et al. [25] verified that the dynamic threshold of cardiovascular hemodynamic parameters predicted by MSET can achieve early warning compared with the traditional fixed threshold method by using simulated data. Recently, Josef Stehlik et al. [24] used an individualized physiological signal analysis platform based on MSET to predict readmission time in patients with heart failure. The platform was able to detect the worsen heart failure caused readmission with 76% to 88% sensitivity and 85% specificity in 100 patients. The median time between initial alarm sent from the platform and readmission was 6.5 (4.2–13.7) days.

Previous studies provide great inspiration and have shown the potential to apply MSET to the CDM. In this study, we aim to establish a process for analyzing the physiological signals collected by a medical-grade wearable device, to build an MSET-based model, and preliminarily verify the effectiveness of MSET to indicate the health condition change of a cohort who has specific chronic diseases. Our key contributions are summarized as follows:

– We preliminarily demonstrate that MSET is able to unveil the latent relationship between the lab examination results and time-series physiological

signals, indicating that physiological signals and MSET promisingly supply added values to the lab examination.
– We leverage the kernel density estimation to characterize the distribution of the residuals obtained from the MSET-based model. Changes in patient health status were quantified by measuring the difference between the two kernel density curves.
– We adopt Cohen Standardized Mean Difference (SMD) [2] and Overlapping Coefficient (OVL) [8] to effectively highlight the difference among the distributions.

2 Materials and Methods

2.1 Multivariate State Estimation Technique (MSET)

MSET is a non-parametric modeling method that estimates the current state of the system based on its historical data, which was originally used for temperature sensor monitoring [23] and further various medical applications [21,24,25]. The core idea of MSET is similarity measurement. It first learns the relationships among parameters of the historical data when the system is running properly. Once a new observation value comes, MSET then leverages the most similar state learned from the historical data to estimate the current state. The key steps of MSET can be formulated as follows:

Step 1: Build the history matrix H based on the historical data.

$$\mathrm{H} = [\mathbf{x}(1), \mathbf{x}(2), \mathbf{x}(3), \ldots, \mathbf{x}(k)] = \begin{bmatrix} x_1(1) & \cdots & x_1(k) \\ \vdots & \ddots & \vdots \\ x_n(1) & \cdots & x_n(k) \end{bmatrix}, \tag{1}$$

where k is the number of observation; $\mathbf{x}(i)$, representing the observation vector at the time i, is defined as:

$$\mathbf{x}(i) = [x_1(i), x_2(i), x_3(i), \ldots, x_n(i)]^{\mathrm{T}}, \tag{2}$$

and $x_n(i)$ denotes the n-th observation value at the time i.

Step 2: Build the memory matrix D. When a new observation vector $\mathbf{x}^{\mathrm{obs}}$ arrives, m observation vectors are selected from H to construct D (set as 10 in our method).

$$\mathrm{D} = [\mathbf{d}_1, \mathbf{d}_2, \ldots \mathbf{d}_m] = \begin{bmatrix} d_{11} & \cdots & d_{1m} \\ \vdots & \ddots & \vdots \\ d_{n1} & \cdots & d_{nm} \end{bmatrix}. \tag{3}$$

Step 3: Calculate the estimation vector $\mathbf{x}^{\mathrm{est}}$.

$$\begin{aligned} \mathbf{x}^{\mathrm{est}} &= \mathrm{D} \cdot \mathbf{w} \\ &= [\mathbf{d}_1, \mathbf{d}_2, \ldots \mathbf{d}_m] \cdot [w_1, w_2 \ldots w_m]^{\mathrm{T}} \\ &= w_1 \mathbf{d}_1 + w_2 \mathbf{d}_2 \ldots + w_m \mathbf{d}_m \end{aligned} \tag{4}$$

It means that $\mathbf{x}^{\text{est}}$ can be represented as the linear combination of the m historical vectors in D. $\mathbf{w}$ can be obtained by minimizing the residual vector $\boldsymbol{\varepsilon}$, which is defined as:

$$\boldsymbol{\varepsilon} = \mathbf{x}^{\text{obs}} - \mathbf{x}^{\text{est}}. \tag{5}$$

We then detail the derivation process of $\mathbf{w}$ using the least squares method.

$$\begin{aligned}\sum_{i=1}^{n} \varepsilon_i^2 = \boldsymbol{\varepsilon}^T \cdot \boldsymbol{\varepsilon} &= \left(\mathbf{x}^{\text{obs}} - \mathbf{x}^{\text{est}}\right)^{\text{T}} \cdot \left(\mathbf{x}^{\text{obs}} - \mathbf{x}^{\text{est}}\right) \\ &= \left(\mathbf{x}^{\text{obs}} - \text{D} \cdot \mathbf{w}\right)^{\text{T}} \cdot \left(\mathbf{x}^{\text{obs}} - \text{D} \cdot \mathbf{w}\right) \\ &= \sum_{i=1}^{n} \left(x^{\text{obs}}(i) - \sum_{\text{j}=1}^{m} w_j d_{ij} \right)^2 .\end{aligned} \tag{6}$$

The partial derivatives of $\sum_{i=1}^{n} \varepsilon_i^2$ in Eq. 6 with respect to $w_1, w_2, \ldots, w_m$ respectively are set equal to 0.

$$\frac{\partial \sum_{i=1}^{n} \varepsilon_i^2}{\partial w_q} = -2 \sum_{i=1}^{n} \left(x^{\text{obs}}(i) - \sum_{\text{j}=1}^{m} w_j d_{ij} \right) d_{iq} = 0, \tag{7}$$

therefore,

$$\sum_{i=1}^{n} x^{\text{obs}}(i) d_{iq} = \sum_{i=1}^{n} \sum_{j=1}^{m} w_j d_{ij} d_{iq} = \sum_{j=1}^{m} \left(\sum_{i=1}^{n} d_{ij} d_{iq} \right) w_j. \tag{8}$$

Equation 8 can be rewritten as the following format:

$$\text{D}^{\text{T}} \cdot \text{D} \cdot \mathbf{w} = \text{D}^{\text{T}} \cdot \mathbf{x}^{\text{obs}}, \tag{9}$$

$$\mathbf{w} = \left(\text{D}^{\text{T}} \cdot \text{D}\right)^{-1} \cdot \left(\text{D}^{\text{T}} \cdot \mathbf{x}^{\text{obs}}\right). \tag{10}$$

Nevertheless, if there exists linear correlation among the vectors in D, $\text{D}^{\text{T}} \cdot \text{D}$ is always not invertible, failing to solve Eq. 10. To resolve this issue, $\mathbf{d}_j$ of D can be projected to a higher dimensional space by the function $\Phi : \mathbb{R}^n \rightarrow \mathbb{R}^z$.

$$\Phi(\text{D})^{\text{T}} \cdot \Phi(\text{D}) \cdot \mathbf{w} = \Phi(\text{D})^{\text{T}} \cdot \Phi\left(\mathbf{x}^{\text{obs}}\right), \tag{11}$$

where $\Phi(\text{D})$ is a $z \times m$ matrix ($z > m$). Therefore, Eq. 9 can be rewritten as:

$$\mathbf{w} = \left(\Phi(\text{D})^{\text{T}} \cdot \Phi(\text{D})\right)^{-1} \cdot \left(\Phi(\text{D})^{\text{T}} \cdot \Phi\left(\mathbf{x}^{\text{obs}}\right)\right). \tag{12}$$

Since $\text{D}^{\text{T}} \cdot \text{D}$ and $\text{D}^{\text{T}} \cdot \mathbf{x}^{\text{obs}}$ can be implemented by a kernel function. We here use kernel function computation ($\otimes$) to update the matrix multiplication in Eq. 12:

$$\mathbf{w} = \left(\text{D}^{\text{T}} \otimes \text{D}\right)^{-1} \cdot \left(\text{D}^{\text{T}} \otimes \mathbf{x}^{\text{obs}}\right). \tag{13}$$

Therefore, the estimation of the current observation value is:

$$\mathbf{x}^{\text{est}} = \mathrm{D} \cdot \left(\mathrm{D}^{\mathrm{T}} \otimes \mathrm{D}\right)^{-1} \cdot \left(\mathrm{D}^{\mathrm{T}} \otimes \mathbf{x}^{\text{obs}}\right), \tag{14}$$

Regarding the kernel function, we select the Gaussian kernel function

$$K(\mathbf{x}, \mathbf{y}; h) = \sum_{i=1}^{n} \frac{1}{\sqrt{2\pi}h} \exp^{-\frac{(x_i - y_i)^2}{2h^2}} \tag{15}$$

Furthermore, we use the regularization to improve the performance of MSET [6]. Equation 13 and Eq. 14 can be revised as follows:

$$\mathbf{w} = \left(\mathrm{D}^{\mathrm{T}} \otimes \mathrm{D} + \lambda \mathrm{I}\right)^{-1} \cdot \left(\mathrm{D}^{\mathrm{T}} \otimes \mathbf{x}^{\text{obs}}\right), \tag{16}$$

$$\mathbf{x}^{\text{est}} = \mathrm{D} \cdot \left(\mathrm{D}^{\mathrm{T}} \otimes \mathrm{D} + \lambda \mathrm{I}\right)^{-1} \cdot \left(\mathrm{D}^{\mathrm{T}} \otimes \mathbf{x}^{\text{obs}}\right). \tag{17}$$

where λ denotes the parameter of regularization; I represents the L2 regularization term.

Step 4: Calculate the residual of the i-th observation value and estimation value.

$$\varepsilon_i = x_i^{\text{obs}} - x_i^{\text{est}}. \tag{18}$$

We then focus on the residual distribution, which is an important measure of the state change.

Step 5: Compute the log-likelihood value using Gaussian mixture model. The authors in [21] designed an indicator based on high-dimensional residual sequence, named Multivariate Health Index (MHI). MHI represents the probability of a new residual vector belonging to the residual distribution of D. That is, we consider the MHI as a *lumped* parameter that is able to represent the overall health status change of the patient.

$$\text{MHI}(\boldsymbol{\varepsilon}) = \log_{10} \frac{1}{\hat{f}(\boldsymbol{\varepsilon})} \tag{19}$$

where

$$\hat{f}(\boldsymbol{\varepsilon}) = \frac{1}{m(2\pi)^{d/2}h^d} \sum_{i=1}^{m} \exp\left(-\frac{\|\boldsymbol{\varepsilon} - \mathbf{r}_i\|}{2h^2}\right), \tag{20}$$

m is the number of columns of D; $\boldsymbol{\varepsilon}$ refers to the residual of the current observation vector; $\mathbf{r}_i$ represents the residual of the i-th column of D; h indicates the width of window; d is the dimension of the observation vector.

2.2 Data Source

We continuously collect the physiological signals of 657 voluntary patients from the general wards of the hyperbaric oxygen department in our hospital using the medical-grade wearable multi-sensor system *SensEcho*, which has been widely used and validated in our previous work [14,17,22,30–32,34,35]. The ECG, chest

& abdominal respiratory waves and triaxial acceleration information of patients were synchronously collected. We collect every patient's physiological data at least at the beginning day and the end day during she/he is hospital. Every collection lasts at least 24 h. The total number of valid physiological series is 1,297, in which 404 patients are collected twice or more. Every participant complied with the protocol approved by the IRB review board (IRB number: S2018-095–01) and signed the printed informed consent. This study was also conducted according to the Declaration of Helsinki. Demographic information was collected by a questionnaire, including age, gender, height and weight.

Since our focus is chronic disease, in this study, the patients who have coronary heart disease with potentially chronic heart failure will construct our in-house dataset of chronic disease patients. According to clinicians' recommendation, we select Brain Natriuretic Peptide (BNP) as the reference lab examination measure because it is an important indicator of heart disease [11,19]. For healthy subjects, the results of BNP examination should be less than 100 pg/ml. On the one hand, physicians suggest that if a patient's BNP decreases by more than 80 pg/ml, the patient is well treated in the hospital. On the other hand, if a patient's BNP ascends more than 200 pg/ml, we believe the treatment effectiveness is not obvious. Thereby, we design the following rules to select satisfactory patient candidates.

- A patient has two or more BNP results;
- The patient's first BNP value is larger than 100 pg/ml;
- The physiological signals of the patient are collected and valid twice or more;
- The patient has at least one BNP result within 2 days before or after the physiological signal collection. If multiple BNP results are available, we include the last one only;
- The descending or ascending level of patient's BNP results is larger than 80 or 200 pg/ml, respectively.

As a result, a total of 17 patients are selected, in which 14 patients' BNP results are improved and 3 patients get worse.

We choose the first collection of physiological signals of patients as the historical data. First, 200 30-second windows of signals are randomly selected to calculate the historical residual values, while the remaining 30s windows of signals construct H. Second, we select 6 representative observation parameters/features (shown in Table 1) to model MSET and then compute the lumped parameter MHI using a Gaussian mixture model (by Eq. 19 and Eq. 20). Third, the last collection of physiological signals of patients is regarded as our test observation data. We extract valid windows of signals and calculate the respective historical and observation residuals. Last, the difference of residual distribution of historical and observation data is measured.

2.3 Data Preprocess and Filtration

The human body is often in a complex dynamic balanced steady-state situation. To ensure the matrix H contains as much health state information as possible,

Table 1. List of six observation physiological parameters

Parameter/Feature	Description
HR mean	Mean heart rate
HR range	Heart rate range
HR std	Heart rate standard deviation
BR mean	Mean breath rate
RESP iqr	Respiratory wave interquartile range
ACT mean	Mean activity level

Table 2. BNP change and SMD/OVL correlation of residual distribution of various physiological parameters

	SMD		OVL	
Parameter	coefficient ρ	$\boldsymbol{p}$	coefficient ρ	$\boldsymbol{p}$
HR mean	0.402	0.109	0.495	**0.043**
HR range	0.571	**0.017**	0.590	**0.013**
HR std	−0.088	0.738	0.587	**0.013**
BR mean	−0.670	**0.003**	0.604	**0.010**
RESP iqr	−0.280	0.277	0.395	0.117
ACT mean	0.082	0.754	0.753	**<0.001**
MHI	0.786	**<0.001**	0.835	**<0.001**

it is necessary to preprocess and filter the data first to weaken the influence of noise and remove the moving segment. In this study, we design the following procedures:

- Perform median filtering on HR and BR;
- Detrend the respiratory wave signals, and then filter them by using the fifth-order low-pass IIR Butterworth filter, whose cut-off frequency was set 2 Hz;
- Split the current signal by non-overlapping sliding window according to preset 30 s observation window;
- The activity level of the subject per second is calculated according to the triaxial acceleration signals, and the activity state of the subject is divided into resting and active according to the numerical value. The observation window will be dropped if the patient status is considered as a movement in this 30s observation window;
- Extract the observation parameters/features of the signals in the remaining observation windows in chronological order and incorporate them in the matrix H;
- Normalize the matrix H by using Min-Max scaling.

2.4 Statistical Method

We leverage kernel density estimation to describe the residual distribution. SMD [2] and OVL [8] are adopted to measure the difference of residual distribution of historical and observation data. In particular, a higher SMD value indicates the difference of two distributions is larger. OVL measures the overlap of two distributions, ranging between 0 (not overlapped) and 1 (fully overlapped). Moreover, for all involved patients, we calculate the BNP change[1] and the SMD & OVL joint distribution of residual distribution of physiological observation values, and compute the Pearson correlation coefficient ρ and its corresponding statistical p-value.

3 Experiment Results

3.1 Group Analysis

Table 2 shows the Pearson correlation coefficient ρ and statistical p-values of SMD and OVL of residual distribution of observation parameters and BNP change. We illustrate the 9 statistically significant parameters ($p < 0.05$) in Fig. 1. As we can see, there exist relationships between BNP change and the residual distribution of these parameters, indicating the possibility of using physiological parameters to infer a patient's state. Specifically, the parameter MHI has the most significant correlation with BNP change. We also find that both SMD and OVL of the BR mean parameter has a high correlation with BNP change. This exposes that a patient's BR has been improved during the second physiological data collection. In addition, the high correlation of ACT mean and BNP change implies the different activity levels between the first and second physiological data collection. When BNP is improved, a patient's activity level rises. This observation is also consistent with the professional consensus about BNP.

3.2 Case Analysis

In this section, we analyze two representative cases in detail.

Case 1. Case 1 is Patient 01 (male, 89 years old, 168 cm, 45 kg). He was in hospital from Oct. 13, 2018 to Oct. 29, 2018. He was diagnosed with heart failure, coronary heart disease, diastolic heart dysfunction, hypertension III, and chronic kidney dysfunction. Figure 2 depicts the timeline of his BNP and physiological signal collection. This patient had the first BNP examination on Oct. 13, 2018 (Day 1), reporting 1685 pg/ml. On Oct. 15, 2018 (Day 3) and Oct. 24, 2018 (Day 12), the first and second collections of this patient's physiological signals were conducted, respectively. On Oct. 26, 2018 (Day 14), the second BNP result

[1] BNP change is computed by subtracting the second BNP examination result from the first one.

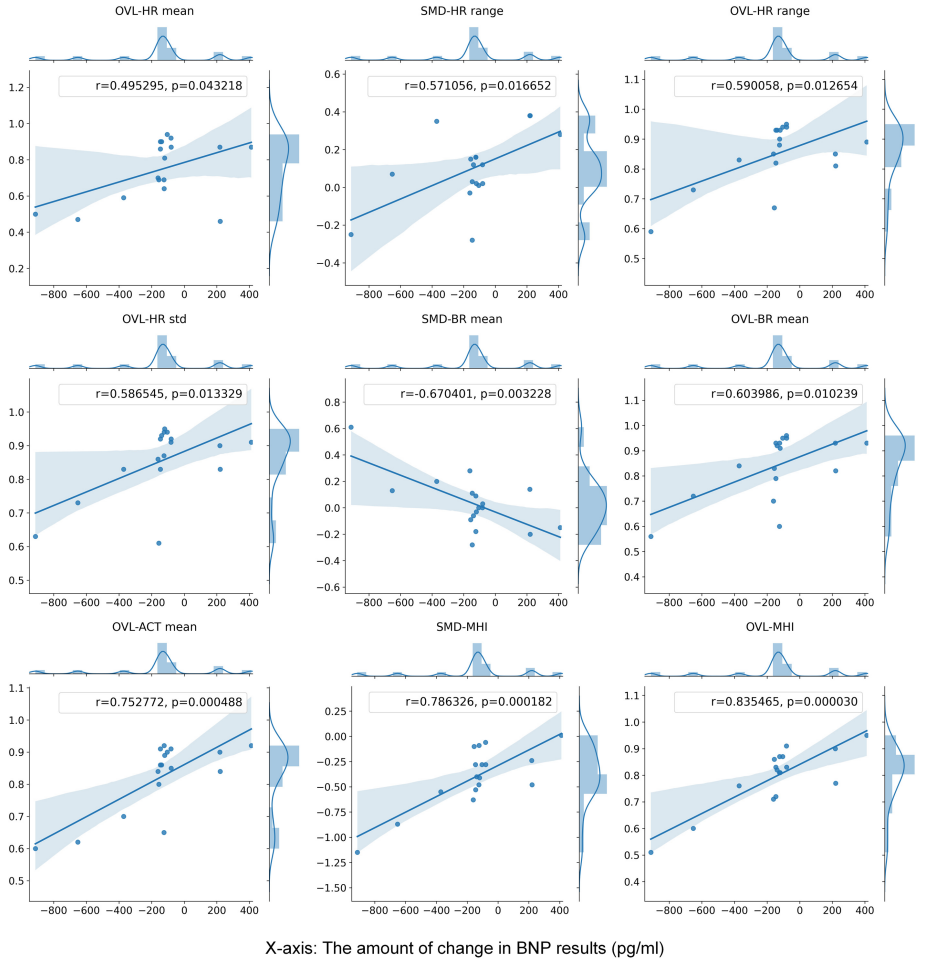

Fig. 1. Joint distribution of SMD and OVL of the residual parameter of observation values and BNP changes

was 772.2 pg/ml, reporting a decrease of 912.8 pg/ml compared with the very first one. During the last 3 hospitalized days, unclear reasons were making the patient's situation worse, but this observation is out of the scope of our protocol described in Sec. 2.2. Figure 3 illustrates the probability density of the residual distribution of various observation parameters, reflecting the difference of the patient's health state during the two physiological signal collections.

Case 2. Case 2 is Patient 15 (male, 84 years old, 167 cm, 62 kg). He was in hospital from Mar. 12, 2019 to Apr. 21, 2019. He was diagnosed with coronary heart disease, ischemic cerebrovascular disease, hypertension II, bronchiectasis coinfection, heart dysfunction, kidney dysfunction, liver dysfunction, moderate ane-

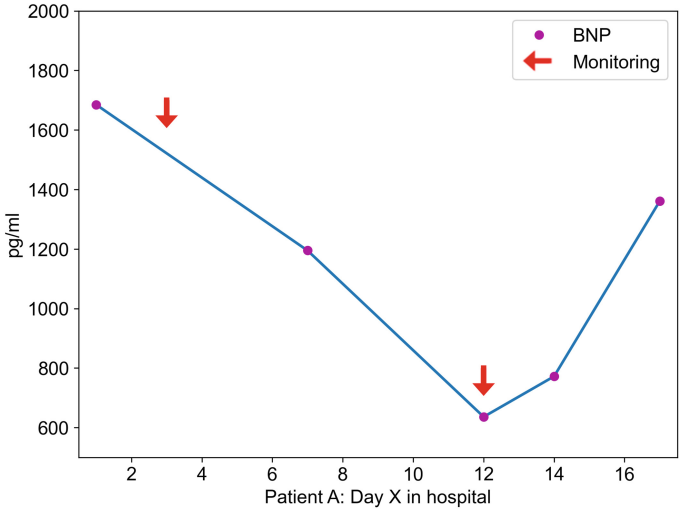

Fig. 2. BNP and physiological signal collection of Patient 01 during his inpatient residence

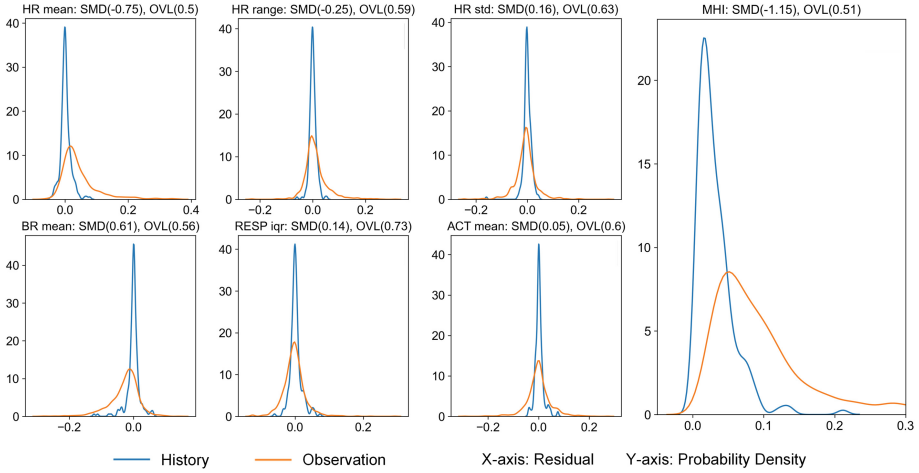

Fig. 3. Residual distribution of historical data and observed data of Patient 01

mia, hypoalbuminemia, and multiple abdominal cavity space-occupying lesions. Figure 4 shows the timeline of his BNP and physiological signal collection. On Mar. 13, 2019 (Day 2), this patient had the first BNP examination, reporting 102.2 pg/ml, and the first physiological signal collection. On Mar. 25, 2019 (Day 14) the second collection of this patient's physiological signals and BNP examination was conducted, reporting 411.3 pg/ml. Unfortunately, we were not able to collect the patient's physiological data since Mar. 25, 2019 (Day 14), even

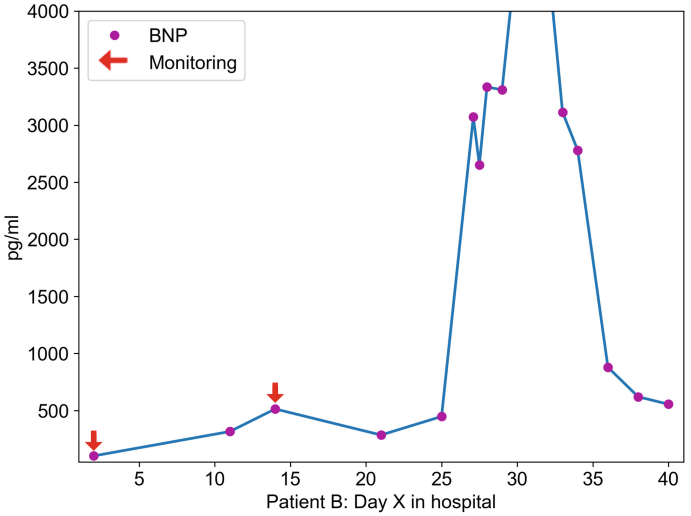

Fig. 4. BNP and physiological signal collection of Patient 15 during his inpatient residence

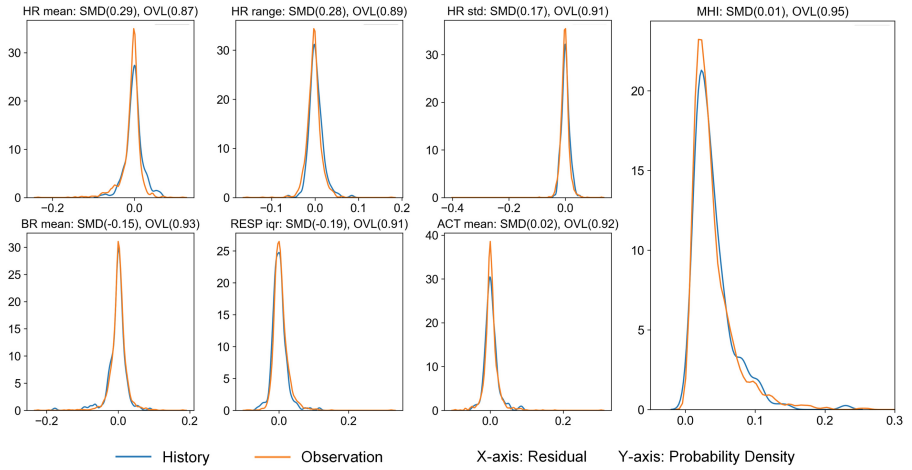

Fig. 5. Residual distribution of historical data and observed data of Patient 15

though his BNP had a dramatic change afterward. This was because he was transferred to the intensive care unit (ICU), where our wearable device was not available. However, we believe that during the two physiological data collections (Day 2–Day 14), the patient's state was not turning better. Figure 5 presents the probability density of residual distribution of various observation parameters, where no significant difference of historical and observation distributions is found.

4 Discussion

This study attempts to evaluate the change of human health and disease status based on physiological signals, which contain a large number of individualized disease and health information. The results preliminarily validate the relationships between physiological signals and lab test results using group and case analysis.

However, different from the industrial mechanical/electronic systems, there is no doubt that human body is a much-complicated system, because a human body is in a dynamic balance of improvement/deterioration all the time. Nowadays, the overall assessment of human health in medicine is based on the combined assessment of multiple laboratory tests (or some specific clinical scale). Nevertheless, the examination timing of these lab tests largely depends on the physician's experience and is difficult to be mathematically quantified. In this pilot study, the lab examination results of BNP were used to approximately indicate the health status of the patients who have the high risk of heart failure, and the change of BNP approximately reveals the change of the health status.

In this paper, we preliminarily explore the efficacy of MSET on a cohort with chronic disease. The experiment results show that a promising relationship between patients' BNP examination values and SMD & OVL of MSET residual distribution. Specifically, MHI has the most significant linear correlation in our results, reporting a coefficient of 0.835 and a p value less than 0.001. The case study indicates that the great potential of using MSET residual distribution as an indicator to distinguish a patient's condition gets better or worse. Our findings suggest that when a patient is admitted to our hospital, her/his physiological signals can be collected on the first day as the baseline, then her/his change of health and disease status is dynamically evaluated afterward. It is expected that this MSET-based approach is highly promising for treatment effect evaluation, as well as providing more abundant information from physiological signals for physicians in CDM.

There also exist some limitations in this study. First, the modeling parameters we used were selected based on experience. More modeling parameters to express the health and disease status of chronic disease patients can be further systematically studied, such as automatic determination of screen parameters of time-series physiological signals. Second, since our data were collected from patients in general wards of the hyperbaric oxygen department, the patients' recovery phase data has a lack of the information from the high dependency unit (HDU) and the intensive care unit (ICU) if the patient's status gets worse, or a lack of the wearable data when the patient is discharged from our hospital. The current data thus does not support us to investigate the model performance when the patient's condition gets worse. Third, chronic disease in the real world is very complicated and patients in the hyperbaric oxygen department always have complex comorbidities, making the cohort volume in the study is relatively small with inevitably confounding factors.

5 Conclusions

In this paper, we conduct a preliminary study to explore the efficacy of MSET on a cohort with chronic disease. The experiment results show that a promising relationship between patients' BNP examination values and SMD & OVL of MSET residual distribution. Specifically, MHI has a more significant linear correlation, reporting a coefficient of 0.835 and a p-value less than 0.001. The case study indicates that the great potential of using MSET residual distribution as an indicator to distinguish a patient's condition gets better or worse. Currently, we are continuously collecting data to expand our in-house dataset, and a more comprehensive analysis will be further performed.

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