A Fuzzy-AR Model to Predict Human Body Weights

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Abstract—This paper proposes a body weight prediction method using Fuzzy-autoregressive (AR) model. New Fuzzy-AR model is formed by including fuzzy membership function which changes AR parameter in autoregressive (AR) model. We employed 452 volunteers, and collected their body weight time-series data during 730 days. We use body weight data from 1st to 365th day as learning data to determine the Fuzzy-AR models. After AR parameters are determined by Yule-Walker equation, we calculate the order, p , of the AR model for each volunteer based on Akaike's Information Criterion (AIC). In our experiment, we predicted body weight change for next p days for those subjects. In the Fuzzy-AR model, we make a fuzzy membership function based on the order of the AR model. As the result, the Fuzzy-AR model obtained higher correlation coefficient between predicted and truth values than the AR model on all volunteers. In addition, the Fuzzy-AR model obtained smaller mean absolute prediction error than the AR model.

Keywords- healthcare system; autoregressive model; prediction model; time-series data; body weight.

I. INTRODUCTION

In general, health care systems provide healthcare services, including screening examinations, prenatal care and infectious disease control. Currently, busy lifestyles including hard work in daily business rise in chronic disease. Examples of chronic disease include the lifestyle diseases. The lifestyle diseases are known as diabetes, high blood pressure, and high blood sugar. These diseases are caused by smoking, alcohol drinking, and obesity. Daily healthcare is needed for preventing the lifestyle disease. To prevent them, health care system for healthy people receives much considerable attentions. Reference [1] pointed that "More than 1 billion people in the world are overweight, and at least 300 million of those are clinically obese. Without action, more than 1.5 billion people are expected to be overweight by 2015." Thus, human body weight control is very important in the world.

In this paper, we consider a personal telehealth system to control body weight of individual. This system collects daily weight data and analyzes them. It finally gives an advice to control the body weight. In [1], this system is the goal, i.e., "Empower individuals and patients to better manage their health by providing them with information regarding their fitness and health through personal medical devices and services."

In our previous work [2], we proposed a Fuzzy-AR model. This Fuzzy-AR model has fuzzy membership function which is constructed based on last p days where p is the order of the AR model. The experiment result showed that this Fuzzy-AR model predicted higher correlation coefficient than AR model. However, this Fuzzy-AR model did not obtain a significant correlation coefficient.

In this study, we propose a prediction method of body weight for next plural days using new Fuzzy-AR model [3]-[7] to solve this problem. The Fuzzy-autoregressive (AR) model proposed here has a fuzzy membership function. The fuzzy membership function controls the magnitude of the coefficient added to maximum AR parameter in autoregressive (AR) model [8]-[10]. We employed 452 volunteers to examine the accuracy. We have body weight data while 730 days from each subject. We use body weight data from 1st to 365th day as learning data to fix the Fuzzy-AR models. Here, after AR parameters are determined by Yule-Walker equation, we calculate the order, p , of the AR model for each volunteer based on Akaike's Information Criterion (AIC) [11], [12]. In the Fuzzy-AR model, we make a fuzzy membership function based on the order of the AR model. In the experiment, we predicted body weight change for next p days. As the result, the Fuzzy-AR model obtained higher correlation coefficient between predicted and truth values than the AR model on all volunteers. In addition, the Fuzzy-AR model obtained smaller mean absolute prediction error than the AR model.

II. PRELIMINARIES

In our study, we use body weight time-series data $x(t)$ ($t = 1, 2, \dots, T$). We collected body weight data while 730 days from each volunteer. T is set to 730 in this study. Body weight data has missing values because it happens that volunteers sometimes forget the measurement. We complement missing values in those data. First, when $x(T)$ is a missing value, we substitute $x(t-i)$ to $x(T)$. Here, the $x(t-i)$ is the latest body weight. Second, when body weight data from $x(2)$ to $x(T)$ are missing values, we obtained complemented body weight by (1).

$$x(t) = \frac{j \times x(t-i) + i \times x(t+j)}{i+j} \quad (1)$$

Figure 1. Flow of proposed method.

III. PROPOSED METHOD

In our study, we use software for statistical analysis R (ver2.12.2). Fig. 1 shows a flow of our proposed method. Step 1 is complement of missing values by (1). In Step 2, we fix AR model and Fuzzy-AR model using body weight data. In step 3, we predict body weight of next p days by AR model and Fuzzy-AR model where p is the order of the AR model.

A. AR Model

The AR model is defined by (2).

$$y(t_x + d) = \sum_{i=1}^p a(i)x(t_x + d - i) + u(t) \quad (2)$$

Here, the notation t_x denotes current time and the notations $y(t)$ and $x(t)$ denote body weights. When $t < t_x$, these body weights are measured body weights, and when $t \geq t_x$, these are predicted values. The notation $a(i)$ does i -th element of AR parameter vector, $\mathbf{a} = (a(1), a(2), \dots, a(i), \dots, a(p))^T$. The notation $u(t)$ does pink noise which amplitude is from -1 to 1, p does the order, d does a integer number during $1 \leq d \leq p$. AR parameter vector, $\mathbf{a}$, is calculated by using Yule-Walker equation defined by (3).

$$\begin{pmatrix} R(0) & R(1) & \cdots & R(p-1) \\ R(1) & R(0) & \cdots & R(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ R(p-1) & R(p-2) & \cdots & R(0) \end{pmatrix} \begin{pmatrix} a(1) \\ a(2) \\ \vdots \\ a(p) \end{pmatrix} = \begin{pmatrix} R(1) \\ R(2) \\ \vdots \\ R(p) \end{pmatrix} \quad (3)$$

Here, the notation $R(i)$ denotes auto covariance function. Moreover, the order, p , is determined on the basis of AIC . In our experiment, the order, p , is determined from the time-series data. We vary p , then calculate the value of AIC by (4) in [11].

$$AIC = -2\ln(L) + 2k \quad (4)$$

Figure 2. Prediction results of AR model for 452 volunteers.

Figure 3. Fuzzy membership function.

Here, L denotes maximum likelihood and k does the number of independently adjusted parameters within the model. Maximum likelihood, L , is changed by k . The order of AR model, p , is determined by the minimum AIC during $[1, d_l]$. Here, the notation d_l is the number of days of the learning data. We predict body weight change for next p days from body weight time-series data of last p days.

B. Fuzzy-AR Model

We predict body weight change of next p days by Fuzzy-AR model proposed in this section. Fig. 2 shows body weight prediction results of the AR model for 452 volunteers. As shown in this figure, the difference between predicted and real value increase with increase of the order of AR model. To solve this problem, we propose a Fuzzy-AR model defined as (5).

$$y(t_x + d) = \sum_{i=1}^p A(i)x(t_x + d - i) \quad (5)$$

In the Fuzzy-AR model, a fuzzy degree is added to weight to the biggest AR element, $\max(\mathbf{a})$. The notation $A(i)$ denotes a Fuzzy-AR element, and it defined by (6).

$$\begin{cases} A(i) = a(i) + \{\mu_w \times a(i) \times u(t)\} & \text{if } a(i) = \max(\mathbf{a}) \\ A(i) = a(i) & \text{otherwise} \end{cases} \quad (6)$$

From Fig. 2, the prediction accuracy of the AR model is decreased according to the increment of the order, p , (Knowledge 1). The maximum AR element, $\max(\mathbf{a})$, strongly

Figure 4. Prediction result by AR model in subject #1. ($p = 6$)

Figure 5. Prediction error by AR model in subject #1. ($p = 6$)

TABLE I. VOLUNTEER'S AGE AND GENDER

Gender	Age							
	20-29	30-39	40-49	50-59	60-69	70-79	80-89	Total
Male	11	96	150	89	48	18	1	413
Female	1	10	12	7	7	2	0	39
Total	12	106	162	96	55	20	1	452

affects to the prediction accuracy (Knowledge 2). From Knowledge 1, a fuzzy IF-THEN rule forms, below.

Rule: IF the order of the AR model, p , is big, THEN the fuzzy degree of weight, μ_w , is high.

Here, the fuzzy IF-THEN rule is described by a fuzzy membership function, $WEIGHT$, as show in Fig. 3. Here, the parameter of the function, p_{max} is the biggest p during all subjects. In this method, we set the p_{max} as 30. The notation p_n denotes the AR order of the interest subject. The fuzzy degree of weight, μ_w in (6), is defined by (7).

$$\mu_w(p) = \min(WEIGHT, S_{p_n}(p)) \quad (7)$$

Here, $S_{p_n}(p)$ is a fuzzy singleton function defined by (8).

$$S_{p_n}(p) = \begin{cases} 1 & \text{if } p = p_n \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Figure 6. Prediction result by Fuzzy-AR model in subject #1. ($p = 6$)

Figure 7. Prediction error by Fuzzy-AR model in subject #1. ($p = 6$)

IV. PREDICTION RESULTS FOR NEXT P DAYS

In our experiment, we employed 452 volunteers as shown in Table I. To test this method, we collected body weight data while 730 days from each subject. We evaluated the proposed Fuzzy-AR model by comparing it with the AR model [10]. Body weight data during [1,365] is used to determine AR model and Fuzzy-AR model. We predicted their body weight change by AR model and Fuzzy-AR model. We evaluated the prediction results by using correlation coefficient and prediction error between predicted and real values. We tested AR model and Fuzzy-AR model 5 times, and calculated the mean and the standard deviation (SD) in correlation coefficient, and mean absolute prediction error.

AR model obtained 0.298 ± 0.273 (mean $\pm$ SD), Fuzzy-AR model did 0.741 ± 0.205 at correlation coefficients. The AR model obtained 1.43 (kg) (2.07 (%)), the Fuzzy-AR model did 0.48 (kg) (0.71 (%)) at absolute error.

We consider the results of subject #1 (male, 43 years old, order of AR model: 6) and subject #2 (male, 39 years old, order of AR model: 7).

The body weights of subject #1 were similarly changed in learning and test period. Fig. 4 shows the prediction results by the AR model and Fig. 5 shows the prediction error by the AR model. Fig. 6 shows the prediction result by the Fuzzy-AR model and Fig. 7 shows the prediction error by the Fuzzy-AR model. Then, this AR model obtained 0.548 ± 0.090 , this Fuzzy-AR model did 0.884 ± 0.001 in correlation coefficient.

Figure 8. Prediction result by AR model in subject #2. ($p = 7$)

Figure 9. Prediction error by AR model in subject #2. ($p = 7$)

Figure 10. Prediction result by Fuzzy-AR model in subject #2. ($p = 7$)

Figure 11. Prediction error by Fuzzy-AR model in subject #2. ($p = 7$)

This AR model obtained 0.99 (kg) (1.18 (%)), this Fuzzy-AR model did 0.49 (kg) (0.59 (%)) in mean absolute prediction error. From Fig. 4 and Fig. 6, we can see that the AR and the Fuzzy-AR model predict the changes. However, the AR model did not predict small daily body weight change. From Fig. 5 and Fig. 7, maximum prediction error was 4.25 (%) in the AR model, 2.35 (%) in Fuzzy-AR model. The number of prediction error were over 1.5 (%) in the AR model, under 1.5 (%) in the Fuzzy-AR model. Thus, we conclude that the Fuzzy-AR model predict smaller prediction error than the AR model in the case of subject #1.

The body weights of subject #2 were different changed in learning and test period. Fig. 8 shows the prediction result by the AR model and Fig. 9 shows the prediction error by the AR model. Fig. 10 shows the prediction result by the Fuzzy-AR model and Fig. 11 shows the prediction error by the Fuzzy-AR model. The AR model obtained 0.371 ± 0.265 , the Fuzzy-AR model did 0.903 ± 0.002 in the correlation coefficients. The AR model obtained 1.08 (kg) (1.69 (%)), the Fuzzy-AR model did 0.42 (kg) (0.66 (%)) in mean absolute prediction error. From Fig. 8 and Fig. 10, the Fuzzy-AR model predicted body weight change. On the other hand, the AR model did not predict body weight change for some days. From Fig. 9 and Fig. 11, the maximum prediction error was 6.44 (%) in the AR model, 2.90 (%) in the Fuzzy-AR model. The number of prediction error were over 2.0 (%) in the AR model, under 2.0 (%) in Fuzzy-AR model. Thus, the Fuzzy-AR model predicted smaller prediction error than the AR model as in the case of subject #1.

Fig. 12 compares correlation coefficient obtained by the AR model with the Fuzzy-AR model on all subjects (452). In Fig. 12, vertical axis is the correlation coefficient obtained by the Fuzzy-AR model, and horizontal axis is the correlation coefficient obtained by the AR model. Fig. 13 compares prediction error obtained by the AR model with that by the Fuzzy-AR model. From Fig. 12, the Fuzzy-AR model predicted higher correlation coefficient than the AR model because most subjects' points were over broken line which shows that equal value between the AR and the Fuzzy AR results. From Fig. 13, the Fuzzy-AR model obtained smaller prediction error than the AR model because most subjects' points were under broken line. Table II and Fig. 14 show the frequency of correlation coefficient. From these results, almost correlation coefficients obtained by the AR model were under 0.5. In contrast, almost correlation coefficients by the Fuzzy-AR model were over 0.5. From these results, the Fuzzy-AR model predicted higher correlation coefficient than the AR model for all subjects. Fig. 15 shows body weight prediction results of the Fuzzy-AR model and the AR model for 452 volunteers. From Fig. 15, we can see that the prediction accuracy was improved with comparison to Fig. 2.

V. CONCLUSIONS

In our study, we predicted body weight change for next p days by the AR model and the Fuzzy-AR model where p is the order of the AR model. We employed body weight data while 730 days of 452 volunteers. The AR model and the Fuzzy-AR model applied 5 times and calculated the means of correlation

Figure 12. Comparison of correlation coefficient.

Figure 13. Comparison of prediction error.

coefficient and prediction error. As the result, the AR model obtained 0.298 ± 0.273 in correlation coefficient between predicted and real values, 1.43 (kg) (2.07 (%)) in absolute prediction error on all subjects. In contrast, the Fuzzy-AR model obtained 0.741 ± 0.205 in correlation coefficient, 0.48 (kg) (0.71 (%)) in mean absolute error. Thus, the Fuzzy-AR model was able to predict higher correlation coefficient and smaller error than the AR model. However, we were not able to see the reason this fuzzy model predict more precisely than standard AR model.

In the future, considering the all results, we try to find the reason and we will apply the Fuzzy-AR model to the time-series data of the other biological information such as the blood-pressure value and body-mass index (BMI). We will

Table II. Frequency of correlation coefficient

Range of correlation coefficient	AR model		Fuzzy-AR model	
	Frequency (times)	Frequency (%)	Frequency (times)	Frequency (%)
$-0.2 \leq \text{cor} < -0.1$	7	1.55	0	0.00
$-0.1 \leq \text{cor} < 0.0$	30	6.64	2	0.44
$0.0 \leq \text{cor} < 0.1$	84	18.58	4	0.88
$0.1 \leq \text{cor} < 0.2$	87	19.25	3	0.66
$0.2 \leq \text{cor} < 0.3$	68	15.04	6	1.33
$0.3 \leq \text{cor} < 0.4$	43	9.51	17	3.76
$0.4 \leq \text{cor} < 0.5$	36	7.96	22	4.87
$0.5 \leq \text{cor} < 0.6$	23	5.09	49	10.84
$0.6 \leq \text{cor} < 0.7$	21	4.65	51	11.28
$0.7 \leq \text{cor} < 0.8$	18	3.98	67	14.82
$0.8 \leq \text{cor} < 0.9$	15	3.32	107	23.67
$0.9 \leq \text{cor} < 1.0$	20	4.42	124	27.43
total	452	100.00	452	100.00

Figure 14. Histogram of correlation coefficient.

Figure 15. Comparison of prediction results for 452 volunteers.

improve prediction accuracy by adding the other attributes such as calories and athletics on the fuzzy model.

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