A Study on Applying an Autoregressive Model with the Kalman Filtering in Accuracy Improvement of Dissolved Oxygen Measurement

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***Abstract*—The dissolved oxygen (DO) measurement plays a crucial role in every automatic aerator-control system for shrimp farming because the DO affects both the animal survival rate and the growth rate. As a consequence, the accuracy degree of the DO sensor matters. The sensor with high accuracy is not economical. Therefore, we propose a framework for accuracy improvement in the DO measurement of the low-cost sensor. The proposed framework is based on the Kalman filtering algorithm in which an autoregressive technique is used to model the state transition. Therefore, it does not require a complex DO dynamic model. Experimental results show that the framework can be used to improve measurement accuracy in most cases. In the best case, our proposed method increases the accuracy by 13.5%. However, the degree of improvement is on a small scale.**

***Index Terms*—Kalman filtering algorithm, autoregressive model, dissolved oxygen measurement, shrimp farming**

Fig. 1. EST DO sensor and optical DO sensor.

I. Introduction

Recently, the intensive aqua-farming has been of interest not only because the world population has been increasing but also because the aquaculture is one of the fastest growing food sectors worldwide [1], [2]. Embedded systems and the information and communication technology (ICT) have been applied for automatic farm-control systems for more than three decades [3]. The fundamental principle underlying automatic control systems for aquaculture is straightforward. Summarily, some crucial parameters are monitored, and, based on the parameter values, the system sends commands to some actuators to control environmental conditions for sustaining animal life [3]–[7].

Many water-quality parameters affect the survival rate and the growth rate of domesticated shrimps, such as the dissolved oxygen (DO), temperature, and pH. Among them, the DO content is one of the most critical factors [8], [9].

Recently, our research group, the Embedded System Technology (EST) laboratory of the National Electronics and Computer Technology Center (NECTEC), proposed a flexible and automatic aerator-control system for shrimp farming in Thailand [7], and one of the crucial parts of the system is the DO sensor. Thus, optical DO sensors with high accuracy were used. Besides, a team of this research group has developed the electrochemical-based DO sensor, as shown in Fig. 1. The mechanism of this sensor is based on a well-known concept of the oxygen-reduction action. In this paper, we hereafter call this sensor the EST sensor after the name of the EST Lab.

As a matter of fact, different technologies utilized in sensor development result in different degrees of accuracy. The EST sensor is economical but less accurate, compared with the optical one. Motived by the fact that we can consider less-accurate data as a noisy signal and that we can extract the signal of interest from a noisy signal by Kalman filtering, we aim to improve the measurement accuracy of the low-cost EST sensor by applying the Kalman filtering together with an autoregressive model. Although there are some related research publications [10], [11], to the best of our knowledge, the Kalman filtering with the autoregressive model has yet to apply for improving the accuracy of the DO measurement in automatic aerator-control systems for shrimp farming.

The rest of this paper is organized as follows. Section II briefly reviews the stand Kalman filtering algorithm and the autoregressive model and describes the framework to be developed in our experiments. Section III details the experiments and results. Section IV discusses the efficiency of the proposed estimator. The last one, Section V, concludes this work.

II. Proposed Framework

This work aims to minimize the difference between DO levels read from EST sensor and those from the optical one. In order to achieve the aim, we adopt the Kalman filtering algorithm together with an autoregressive technique, which is used to model the state transition of the DO concentration in shrimp ponds. The following subsections briefly review the background information about the Kalman filtering and the autoregressive model, and the last subsection sketches the proposed framework used in our simulations.

A. Kalman Filtering

The Kalman filtering algorithm can be used to estimate the state of a linear system with random behavior [12]–[14]. It assumes that the linear system is described by a state equation together with a measurement equation. The state equation and the measurement equation are formulated by the following equations, respectively.

$$\boldsymbol{x}_k = \boldsymbol{F}_{k-1}\boldsymbol{x}_{k-1} + \boldsymbol{G}_{k-1}\boldsymbol{u}_{k-1} + \boldsymbol{w}_{k-1}, \tag{1}$$

$$\boldsymbol{y}_k = \boldsymbol{H}_k\boldsymbol{x}_k + \boldsymbol{v}_k, \tag{2}$$

where $\boldsymbol{x}_k$ is the state vector at time k, $\boldsymbol{F}$ is the state-transition matrix, $\boldsymbol{u}$ is the control input vector, $\boldsymbol{G}$ is the control input matrix, $\boldsymbol{w}$ is the process noise vector, $\boldsymbol{y}_k$ is the vector of measured outputs, $\boldsymbol{H}$ is the observation matrix, and $\boldsymbol{v}_k$ is the measurement white-noise vector. Note that the matrix $\boldsymbol{F}$ is a square matrix, and it applies the effect of each state parameter at time $k-1$ on the state parameter at time k. The matrix $\boldsymbol{G}$ applies the effect of each control input parameter on the state. The matrix $\boldsymbol{H}$ describes the relationship between the state vector $\boldsymbol{x}_k$ and the measurement vector $\boldsymbol{y}_k$.

The Kalman filtering algorithm consists of two stages: prediction and measurement update. The prediction stage consists of two steps: state vector prediction and state error covariance prediction. In the first step, given an initial state estimate $\hat{\boldsymbol{x}}_0$ and an initial state error covariance matrix $\boldsymbol{P}_0$, the predicted state vector $\hat{\boldsymbol{x}}_{k|k-1}$ (called *a priori* predicted state vector) is predicted from the state dynamic equation

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{F}_{k-1}\hat{\boldsymbol{x}}_{k-1} + \boldsymbol{G}_{k-1}\boldsymbol{u}_{k-1}, \tag{3}$$

where $\hat{\boldsymbol{x}}_{k-1}$ is the previous estimated state vector.

In the second step, the state error covariance matrix $\boldsymbol{P}_{k|k-1}$ is predicted by

$$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_{k-1}\boldsymbol{P}_{k-1}\boldsymbol{F}_{k-1}^{\mathrm{T}} + \boldsymbol{Q}_{k-1}, \tag{4}$$

where $\boldsymbol{Q}_{k-1}$ is the covariance matrix of process noise at time $k-1$, and $\boldsymbol{P}_{k-1}$ is the state error covariance of the state vector $\boldsymbol{x}_{k-1}$, which is defined as

$$\boldsymbol{P}_{k-1} = E\left[(\boldsymbol{x}_{k-1} - E\left[\boldsymbol{x}_{k-1}\right])(\boldsymbol{x}_{k-1}^{\mathrm{T}} - E\left[\boldsymbol{x}_{k-1}^{\mathrm{T}}\right])\right]. \tag{5}$$

Note that the symbol $E[\cdot]$ denotes the expectation of state vectors, and the superscript $_{\mathrm{T}}$ denotes the matrix transposition.

The measurement update stage consists of three steps: Kalman gain determination, state vector update, and state error covariance update. In the first step, the Kalman gain matrix $\boldsymbol{K}_k$ is computed by

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{\mathrm{T}}(\boldsymbol{H}_k\boldsymbol{P}_{k|k-1}\boldsymbol{H}_k^{\mathrm{T}} + \boldsymbol{R}_k)^{-1}, \tag{6}$$

where $\boldsymbol{R}_k$ is the covariance matrix of measurement noise at time k.

Second, the Kalman gain matrix is used to update the state vector $\hat{\boldsymbol{x}}_k$ by

$$\hat{\boldsymbol{x}}_k = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k(\boldsymbol{y}_k - \boldsymbol{H}_k\hat{\boldsymbol{x}}_{k|k-1}). \tag{7}$$

Third, the state error covariance matrix $\boldsymbol{P}_k$ (called *a posteriori* error covariance matrix) is updated by

$$\boldsymbol{P}_k = \boldsymbol{P}_{k|k-1} - \boldsymbol{K}_k\boldsymbol{H}_k\boldsymbol{P}_{k|k-1}. \tag{8}$$

We can therefore use the Kalman filtering algorithm to estimate the state vector $\hat{\boldsymbol{x}}_k$ for any k when the initial values of $\hat{\boldsymbol{x}}_0$ and $\boldsymbol{P}_0$ are given.

B. Autoregressive Model

The autoregressive model (AR) can be used to represent a time-varying process in nature with the assumption that its output depends on its previous values and a stochastic term [15]. Let AR(p) denote an AR of order p. Then, according to AR(p), the variable X at time t, denoted by X_t, is a function of p previous Xs, i.e., from X_{t-p} to X_{t-1}, and can be formulated by the following equation.

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t, \tag{9}$$

where c is a constant, φ_i for $i=1$ to p are the coefficients of the model, and ε_t is white noise.

In this work, we use AR(p) to model the state transition in the prediction stage of the Kalman filtering algorithm.

C. Proposed Framework Based on the Kalman Filtering and the Autoregressive Model

Based on the Kalman filtering algorithm, our proposed framework utilizes AR(p) in the prediction stage, and it follows eight steps as illustrated in Fig. 2. Note that the input of AR(p) (which is also the input of the prediction stage) and the output measurement vector (which can be considered as the input of the measurement update stage) are data obtained from EST sensors. Experiments and simulation details are provided in the next section.

III. Experiments and Results

In order to obtain the data used in our simulations, we set two experiment ponds and nurtured whiteleg shrimps (*Litopenaeus vannamei*). The details of experimental conditions, experiments, and results are provided in the following subsections.

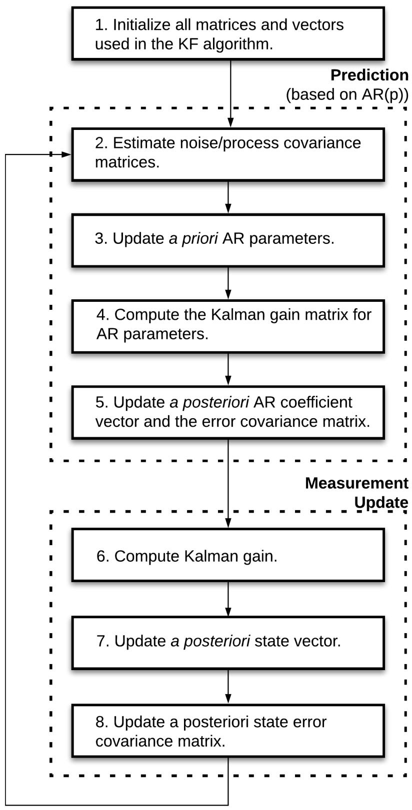

Fig. 2. Framework of the Kalman filtering (KF) with AR(p) that is used to model the state transition of the DO content.

A. Experimental Setup and Conditions

We adopted two cylindrical plastic containers and used them as the experiment ponds, of which their diameters and heights are 1.2 meters and 0.8 meters, respectively. 120 three-gram whiteleg shrimps were nurtured for 50 days until their weights were about 15 grams. The ponds were in an open-air condition, and some water-quality parameters were controlled as follows. The salinity was controlled to be 17 parts per thousand, the pH was in the range of 7.5 to 8.5, the alkalinity was in the range of 130 to 150 mg/L, and the total ammoniacal nitrogen was controlled to be less than 1 mg/L.

Both ponds were equipped with a circular pump, which was used to increase the DO content, and a few DO sensors from which data were read and recorded every one minute.

Two sets of DO data were used in our simulations; one was obtained when the ponds had no shrimp (but the pumps were in operation), and another was obtained when the ponds housed 120 shrimps. The dates on which these data were read and data labels are shown in Table I.

In this work, we conducted three experiments, and each experiment had a set of specific assumptions. Note that, in all simulations, we set the length of the moving average that was applied to the data to be 30 and the length of the look-back window used while performing the EWMA to be 15 in order to estimate the process covariance matrix $\boldsymbol{Q}$ and the noise covariance matrix $\boldsymbol{R}$. We did not investigate the effects of these two parameters in this report.

TABLE I
DATA AND THEIR LABELS USED IN OUR SIMULATIONS. NOTE THAT THE CODE 'DATA $XXYZ$' SHOULD BE READ 'THE DATA NO. XX OBTAINED FROM THE EST SENSOR NO. Y WHEN THE POND HAS NO SHRIMP ($Z=$N) OR WHEN THE POND HOUSES 120 SHRIMPS ($Z=$S).'

	Date	**Label**	
		Sensor 1	**Sensor 2**
No shrimp	2-4 July 2017	Data 011N	Data 012N
	7-9 July 2017	Data 021N	Data 022N
	10-12 July 2017	Data 031N	Data 032N
	16-17 July 2017	Data 041N	Data 042N
	21-23 July 2017	Data 051N	Data 052N
120 shrimps	11-13 August 2017	Data 061S	Data 062S
	14-16 August 2017	Data 071S	Data 072S
	19-21 August 2017	Data 081S	Data 082S
	23-25 August 2017	Data 091S	Data 092S
	14-16 September 2017	Data 101S	Data 102S

B. Experiment 1: DO Content Estimation Based on Data Obtained from One Sensor

In this simulation, we assumed that only data obtained from one DO sensor were available. Thus, we took those data as the output measurement vector of the Kalman filtering algorithm. Also, the state transition was modeled by AR(p), of which its variable X_t was predicted from its previous p values that were taken from the same data.

We compared the estimated DO concentration values with those obtained from the optical sensor, calculated root-mean-square error (RMSE) values between them, and used those RMSE values to indicate the efficiency of our Kalman-filtering-based estimator and, consequently, the accuracy improvement of the DO measurement. Also, the effect of the order p of AR(p) on the efficiency was investigated.

Simulation results are shown in Table II and Table III.

It can be seen from the tables that, on average, using the Kalman filtering can slightly improve the accuracy because it causes the RMSE drops marginally. Besides, the order p of AR(p) seems not to affect the efficiency of the Kalman filtering in this experiment.

C. Experiment 2: DO Content Estimation Based on the Average of Data Obtained from Two Sensors

In the second simulation, we assumed that there were two EST sensors and the averaged data from both were used as the output measurement vector in the Kalman filtering. Similarly, the state transition was modeled by using AR(p), of which its variable was predicted based on the same averaged data. Simulation results are shown in Table IV and Table V.

We found the similar conclusion, i.e., using the Kalman filtering could slightly improve the accuracy on average, and the order of AR(p) did not significantly affect the efficiency of the estimator.

TABLE II
RMSE BETWEEN DO LEVELS OBTAINED FROM THE OPTICAL SENSOR AND THOSE OBTAINED FROM THE EST SENSOR WITH (W) AND WITHOUT (W/O) THE KALMAN FILTERING (KF) WHEN NO SHRIMP WAS DOMESTICATED IN THE PONDS.

	AR(1)		AR(2)		AR(3)		AR(4)		AR(5)	
	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF
Data 011N	0.4863	0.4885	0.4861	0.4885	0.4861	0.4885	0.4864	0.4885	0.4868	0.4885
Data 021N	0.1260	0.1275	0.1274	0.1275	0.1276	0.1275	0.1276	0.1275	0.1279	0.1275
Data 031N	0.1312	0.1332	0.1327	0.1332	0.1337	0.1332	0.1345	0.1332	0.1347	0.1332
Data 041N	0.2135	0.2151	0.2142	0.2151	0.2150	0.2151	0.2154	0.2151	0.2160	0.2151
Data 051N	0.2598	0.2696	0.2597	0.2696	0.2595	0.2696	0.2592	0.2696	0.2589	0.2696
Data 012N	0.3809	0.3823	0.3816	0.3823	0.3819	0.3823	0.3824	0.3823	0.3831	0.3823
Data 022N	0.1192	0.1209	0.1212	0.1209	0.1221	0.1209	0.1223	0.1209	0.1226	0.1209
Data 032N	0.1565	0.1578	0.1581	0.1578	0.1590	0.1578	0.1598	0.1578	0.1591	0.1578
Data 042N	0.2468	0.2479	0.2478	0.2479	0.2487	0.2479	0.2494	0.2479	0.2493	0.2479
Data 052N	0.3783	0.3813	0.3781	0.3813	0.3782	0.3813	0.3782	0.3813	0.3782	0.3813
Average	0.2498	0.2524	0.2507	0.2524	0.2512	0.2524	0.2515	0.2524	0.2517	0.2524
SD	0.1275	0.1278	0.1268	0.1278	0.1265	0.1278	0.1264	0.1278	0.1266	0.1278

TABLE III
RMSE BETWEEN DO LEVELS OBTAINED FROM THE OPTICAL SENSOR AND THOSE OBTAINED FROM THE EST SENSOR WITH (W) AND WITHOUT (W/O) THE KALMAN FILTERING (KF) WHEN 120 SHRIMPS WERE DOMESTICATED IN THE PONDS.

	AR(1)		AR(2)		AR(3)		AR(4)		AR(5)	
	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF
Data 061S	0.7238	0.7232	0.7240	0.7232	0.7243	0.7232	0.7245	0.7232	0.7250	0.7232
Data 071S	0.2238	0.2358	0.2255	0.2358	0.2263	0.2358	0.2276	0.2358	0.2288	0.2358
Data 081S	0.3664	0.3704	0.3703	0.3704	0.3740	0.3704	0.3728	0.3704	0.3736	0.3704
Data 091S	0.1696	0.1916	0.1688	0.1916	0.1678	0.1916	0.1671	0.1916	0.1670	0.1916
Data 101S	1.2740	1.2747	1.2740	1.2747	1.2742	1.2747	1.2746	1.2747	1.2750	1.2747
Data 062S	0.9345	0.9328	0.9364	0.9328	0.9385	0.9328	0.9393	0.9328	0.9411	0.9328
Data 072S	0.3650	0.3668	0.3649	0.3668	0.3655	0.3668	0.3663	0.3668	0.3672	0.3668
Data 082S	0.4023	0.4028	0.4040	0.4028	0.4052	0.4028	0.4061	0.4028	0.4075	0.4028
Data 092S	0.2075	0.2144	0.2077	0.2144	0.2079	0.2144	0.2082	0.2144	0.2086	0.2144
Data 102S	1.2333	1.2362	1.2335	1.2362	1.2339	1.2362	1.2346	1.2362	1.2351	1.2362
Average	0.5900	0.5949	0.5909	0.5949	0.5918	0.5949	0.5921	0.5949	0.5929	0.5949
SD	0.4231	0.4190	0.4229	0.4190	0.4230	0.4190	0.4231	0.4190	0.4232	0.4190

D. Experiment 3: DO Content Estimation Based on Data Obtained from Two Sensors

We did something differently in the last simulation. We still assumed that data obtained from two EST sensors were available, as the previous experiment. However, instead of using the same vector as the output measurement vector and the input of AR(p), we used one as the former and another as the latter. This scheme raised a problem of the choice of sensor selection to be used in the AR(p). We came around this problem by deploying a simple strategy, i.e., choosing the data with a higher average value as the input of the AR(p). It was because we noticed that, in most instances, the data (which were available to us) obtained from EST sensors were lower than those obtained from the optical one. Therefore, selecting the data with a higher average value as the input of the AR(p) might bring the estimated values close to those obtained from the optical sensor.

Simulation results are shown in Table VI and Table VII. It can be seen that when there was no shrimp in the ponds, using the Kalman filtering could slightly improve the accuracy on average. Comparing the results in Table VI with those shown in Table IV, we found that, when there were two sensors and when AR(1) was used to model the state transition, we could get the minimum average RMSE value (0.2264) if we had adopted the framework used in Experiment 3. However, using the Kalman filtering caused the average RMSE values to increase marginally when the ponds housed the shrimps, as shown in Table VII.

IV. DISCUSSION

All simulation results in this work suggest that the proposed framework can be used to improve the accuracy of DO measurement in most cases, especially in the case that there is more than one sensor available. However, the degree of improvement is averagely not of significance.

Comparing Table II and Table III, Table IV and Table V, and Table VI and Table VII, we found that the RMSE values increased when there were shrimps in the experiment ponds. A reason might be that, during domesticating the animal, there are many factors in action, and they affect the DO concentration. Thus, the effects of these factors should be investigated and taken into consideration in the DO dynamic model. Therefore, when there are shrimps in the pond, the

TABLE IV

RMSE BETWEEN DO LEVELS OBTAINED FROM THE OPTICAL SENSOR AND THOSE OBTAINED FROM TWO EST SENSORS WITH (W) AND WITHOUT (W/O) THE KALMAN FILTERING (KF) WHEN NO SHRIMP WAS DOMESTICATED IN THE PONDS.

	AR(1)		AR(2)		AR(3)		AR(4)		AR(5)	
	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF
Data 011N & Data 012N	0.4195	0.4207	0.4196	0.4207	0.4198	0.4207	0.4204	0.4207	0.4210	0.4207
Data 021N & Data 022N	0.1161	0.1160	0.1169	0.1160	0.1177	0.1160	0.1178	0.1160	0.1183	0.1160
Data 031N & Data 032N	0.1337	0.1335	0.1354	0.1335	0.1362	0.1335	0.1366	0.1335	0.1368	0.1335
Data 041N & Data 042N	0.2285	0.2288	0.2293	0.2288	0.2299	0.2288	0.2302	0.2288	0.2307	0.2288
Data 051N & Data 052N	0.3140	0.3165	0.3140	0.3165	0.3139	0.3165	0.3138	0.3165	0.3138	0.3165
Average	0.2423	0.2431	0.2430	0.2431	0.2435	0.2431	0.2438	0.2431	0.2441	0.2431
SD	0.1270	0.1278	0.1264	0.1278	0.1261	0.1278	0.1261	0.1278	0.1262	0.1278

TABLE V

RMSE BETWEEN DO LEVELS OBTAINED FROM THE OPTICAL SENSOR AND THOSE OBTAINED FROM TWO EST SENSORS WITH (W) AND WITHOUT (W/O) THE KALMAN FILTERING (KF) WHEN 120 SHRIMP WERE DOMESTICATED IN THE PONDS.

	AR(1)		AR(2)		AR(3)		AR(4)		AR(5)	
	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF
Data 061S & Data 062S	0.6243	0.6235	0.6258	0.6235	0.6275	0.6235	0.6290	0.6235	0.6311	0.6235
Data 071S & Data 072S	0.2443	0.2469	0.2451	0.2469	0.2456	0.2469	0.2466	0.2469	0.2477	0.2469
Data 081S & Data 082S	0.3666	0.3664	0.3689	0.3664	0.3707	0.3664	0.3705	0.3664	0.3715	0.3664
Data 091S & Data 092S	0.1559	0.1648	0.1559	0.1648	0.1558	0.1648	0.1561	0.1648	0.1564	0.1648
Data 101S & Data 102S	1.2455	1.2467	1.2458	1.2467	1.2463	1.2467	1.2468	1.2467	1.2473	1.2467
Average	0.5273	0.5296	0.5283	0.5296	0.5292	0.5296	0.5298	0.5296	0.5308	0.5296
SD	0.4385	0.4367	0.4384	0.4367	0.4384	0.4367	0.4385	0.4367	0.4385	0.4367

TABLE VI

RMSE BETWEEN DO LEVELS OBTAINED FROM THE OPTICAL SENSOR AND THOSE OBTAINED FROM TWO EST SENSORS WITH (W) AND WITHOUT (W/O) THE KALMAN FILTERING (KF) WHEN NO SHRIMP WAS DOMESTICATED IN THE PONDS. THE ENTRIES IN THE FIRST COLUMN ARE DATA USED AS THE INPUT OF AR(p), WHEREAS THOSE IN THE SECOND ARE USED AS THE OUTPUT MEASUREMENT VECTOR.

		AR(1)		AR(2)		AR(3)		AR(4)		AR(5)	
Input of AR(p)	Measurement	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF
Data 012N	Data 011N	0.3938	0.4885	0.4618	0.4885	0.4203	0.4885	0.4257	0.4885	0.4264	0.4885
Data 021N	Data 022N	0.1274	0.1209	0.1261	0.1209	0.1278	0.1209	0.1265	0.1209	0.1269	0.1209
Data 031N	Data 032N	0.1220	0.1578	0.1427	0.1578	0.1397	0.1578	0.1418	0.1578	0.1432	0.1578
Data 041N	Data 042N	0.2201	0.2479	0.2231	0.2479	0.2260	0.2479	0.2283	0.2479	0.2303	0.2479
Data 051N	Data 052N	0.2686	0.3813	0.2917	0.3813	0.2897	0.3813	0.2986	0.3813	0.3041	0.3813
Average		0.2264	0.2793	0.2491	0.2793	0.2407	0.2793	0.2442	0.2793	0.2462	0.2793
SD		0.1124	0.1541	0.1362	0.1541	0.1202	0.1541	0.1229	0.1541	0.1234	0.1541

Kalman filtering does not seem to improve the accuracy. On the other hand, when there is no shrimp in the pond, our proposed method can improve the accuracy, in the best case, by approximately 13.5%. The best case is the case in which data obtained from one DO sensor are used as the input of AR(p) and those obtained from another are used as the output measurement vector. The best case is shown in Table VI.

V. CONCLUSION

This paper reported the study on applying the Kalman filtering and the autoregressive model to improve the accuracy of DO measurement in the automatic aerator-control system for shrimp farming. The Kalman filter algorithm was used as a basis of the proposed framework, in which the autoregressive model was used to model the state transition. It aimed to minimize the difference between DO levels read from the economical but less accurate sensor and those read from the more accurate one. The simulation results showed that using the Kalman filtering with the autoregressive model could improve the accuracy of DO measurement on a small scale. In the best case, our proposed method increases the accuracy by 13.5%.

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TABLE VII

RMSE BETWEEN DO LEVELS OBTAINED FROM THE OPTICAL SENSOR AND THOSE OBTAINED FROM TWO EST SENSORS WITH (W) AND WITHOUT (W/O) THE KALMAN FILTERING (KF) WHEN 120 SHRIMPS WERE DOMESTICATED IN THE PONDS. THE ENTRIES IN THE FIRST COLUMN ARE DATA USED AS THE INPUT OF AR(p), WHEREAS THOSE IN THE SECOND ARE USED AS THE OUTPUT MEASUREMENT VECTOR.

		AR(1)		AR(2)		AR(3)		AR(4)		AR(5)	
Input of AR(p)	Measurement	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF	w/ KF	w/o KF
Data 062S	Data 061S	0.8153	0.7232	0.8022	0.7232	0.7696	0.7232	0.7326	0.7232	0.7271	0.7232
Data 072S	Data 071S	0.3941	0.2358	0.3645	0.2358	0.3843	0.2358	0.3493	0.2358	0.3643	0.2358
Data 081S	Data 082S	0.4102	0.4028	0.4038	0.4028	0.4076	0.4028	0.4017	0.4028	0.4009	0.4028
Data 092S	Data 091S	0.2400	0.1916	0.2456	0.1916	0.2295	0.1916	0.2272	0.1916	0.2230	0.1916
Data 102S	Data 101S	1.2515	1.2747	1.2612	1.2747	1.2628	1.2747	1.2664	1.2747	1.2555	1.2747
Average		0.6222	0.5656	0.6155	0.5656	0.6108	0.5656	0.5954	0.5656	0.5942	0.5656
SD		0.4112	0.4480	0.4173	0.4480	0.4148	0.4480	0.4191	0.4480	0.4132	0.4480

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