A Noise Suppression of LSTM algorithm combined with Kalman filter for Agriculture Automation

Abdoulaye Barry
Computer Science and Information Technology,
University of the District of Columbia
Washington, DC, USA
abdoulaye.barry@udc.edu

Junwhan Kim
Computer Science and Information Technology,
University of the District of Columbia
Washington, DC, USA
junwhan.kim@udc.edu

Byunngu Yu
Computer Science and Information Technology,
University of the District of Columbia
Washington, DC, USA
byu@udc.edu

Sabine O'Hara
College of Agriculture, Urban Sustainability and Environmental Sciences,
University of the District of Columbia
Washington, DC, USA
sabine.ohara@udc.edu

ABSTRACT

An immense volume of data is produced by sensor devices in the fields of aquaponics, hydroponics, and soil-based food production, where these devices track various environmental factors. Data stream mining is the method of retrieving data from fast-sampled data sources that are constantly streaming. The accuracy of data obtained through data stream mining is largely determined by the algorithm utilized to filter out noise. For threshold-based automation, an actuator can be activated when the value of sensor data is above a permissible threshold. Noise from sensors may activate the actuator. Several statistical and machine learning-based noise-suppression algorithms have been proposed in the literature. They have been evaluated based on the mean squared error metric (MSE). The Long Short-Term Memory – LSTM filter (MSE: 0.000999943) performs better noise suppression than other traditional filters – Kalman (MSE: 0.0015982). We propose a new noise suppression filter – LSTM combined with Kalman (LSTM-KF). In LSTM-KF, the Kalman filter acts as an encoder and the LSTM becomes the decoder, resulting in a significantly lower MSE – 0.000080789592. The LSTM-KF is installed in our threshold-based aquaponics automation to maximize sustainable food production at minimum cost.

CCS CONCEPTS

• Information systems; **• Data management systems**; **• Information integration**; **• Extraction, transformation and loading**;

KEYWORDS

Machine Learning, Kalman Filter, Agriculture Automation

Conference acronym 'ICMLT, March 10–12, 2023, Stockholm, Sweden

ACM ISBN 978-1-4503-9833-6…$15.00
https://doi.org/XXXXXXX.XXXXXXX

ACM Reference Format:
Abdoulaye Barry, Junwhan Kim, Byunngu Yu, and Sabine O'Hara. 2018. A Noise Suppression of LSTM algorithm combined with Kalman filter for Agriculture Automation. In *Proceedings of 2023 8th International Conference on Machine Learning Technologies (Conference acronym 'ICMLT).* ACM, New York, NY, USA, 5 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

Aquaponics is a method of agricultural production that combines aquaculture (fish production) with hydroponics (soil-less production in nutrient rich water) and creates a system in which nutrients from a recirculating fish rearing system serve as fertilizer for food plants. Urban aquaponics holds the promise of not only introducing agricultural production to land-poor settings, but also of generating solutions to the food insecurity prevalent in low urban neighborhoods where access to fresh, unprocessed food has been limited. The food insecurity facing urban and metro areas, where close to 80 percent of US consumers live, was heightened during the recent COVID pandemic which disrupted food supply chains [1, 2].

As migrant workers were unable to gain access to harvest produce, food processing plants experienced high rates of COVID outbreaks, and consumers in low-income neighborhoods were unable to afford food delivery costs, the U.S. food supply was disrupted both on the supply and the demand side. These added food security burdens further acerbated high levels of food insecurity. Especially hard hit were households with children who no longer received their school meals during the pandemic.

This added urgency to the question whether and how urban aquaponics can improve food insecurity and the high rates of food related illness observed in food insecure neighborhoods [2]. Research conducted in over 3000 counties in the United States found, for example, that COVID fatalities were higher in counties with high rates of diabetes and heart disease [2]. One of the social determinants of food related illness is income with low income neighrbohoods suffering disproportionately high levels of food related illness and this increased vulnerability to other health related shocks like the COVID pandemic. Given the limited purchasing power in food insecure neighborhoods, the commercial viability of urban aquaponic and hydroponic systems has been called into question.

This lends further urgency to technological advances that can increase the efficiency and reliability of urban aquaponic production.

However, increasing the efficiency and reliability of urban food production requires complex agricultural knowledge and hands-on experience. This is especially true for aquaponic production which requires the integration of aquaculture and hydroponics systems. To optimize aquaponic production is considerably more complex than to optimize aquaculture production or hydroponic production. Aquaponics has therefore remained less efficient than aquaculture and hydroponics [7]. In light of persistent increases in fertilizer costs and nutrient shortages, aquaponics may be on the verge of becoming more profitable provided the efficiency and reliability of the production methods can be further improved. Machine learning may offer tremendous opportunities for efficiency gains a greater stability as the optimization of two systems (aquaculture and hydroponics) can be advanced by identifying complex patterns and relationships that may otherwise be hidden.

To maximize sustainable food production at minimum cost, we have developed next-generation aquaponics automation based on the most recent neural network models. The Internet-of-Things (IoT) is beginning to impact a wide array of sectors and industries including agriculture to reduce inefficiencies and to improve the performance [12]. Our aquaponics automation based on the capabilities offered by IoT consists of agricultural sensors devices, actuators, wireless modules, and data management.

Enormous amounts of data are generated each day by the sensor devices. These devices continuously monitor numerous environmental properties of the aquaponics system. Data stream mining is the process of extracting data from continuous, rapidly sampled data sources. The data accuracy that can be achieved in data stream mining is highly dependent on the algorithm chosen to suppress noise. Several statistical and machine learning-based noise- suppression algorithms have been proposed in the literature [10, 11]. The longer-term dependencies of the data streams from agriculture sensors have been considered in [11]. A Kalman filter training algorithm has reduced the number of training steps when compared to the gradient decent training approach in the Long Short-Term Memory (LSTM) network [13]. Motivated by the effectiveness of LSTM combined with the Kalman filter, we propose a new machine learning-based noise suppression approach, called LSTM combined with Kalman filter (LSTM-KF). The main contribution is that an LSTM-KF model is applied for noise suppression of agriculture sensors in a large-scale aquaponics system. We show that the LSTM-KF performs better than decoupled LSTM and Kalman filters.

The rest of this paper is organized as follows. We overview related efforts in Section 2. In Sections 3 and 4, we explain our proposed method and empirical results, respectively. The paper is concluded with Section 5.

2 RELATED WORK

The use of computer and sensor-based automation has led to a remarkable improvement in agricultural productivity [8]. However, the reliability of the data generated by these sensors is often hampered by sensor-specific noise. Several approaches have been proposed to address this issue, but their effectiveness depends on the specific type of data. This section aims to review the current state of machine learning-based filtering methods for various types of agricultural data to reduce sensor noise.

Jiang et. al. proposed LSTM based adaptive filtering [**?**] by learning the weight variations from the weight sequence directly. The trained networks are used to regulate the weights generated by conventional filtering schemes for reduced prediction error of hyperspectral images. This filter models not only the correlations between pixels from different spectral bands, but also the temporal dependencies of the filtering weights. This approach has not been evaluated with data streams from real sensors.

As another recent research activity, a new target tracking filter using deep learning has been proposed by Cui et. al. [9]. The filter is developed in a unified neural network including feedforward, recurrent, and attention neural network structures to resolve tracking problems. The proposed filter in [9] has been simulated to estimate a target state.

As a transition algorithm, the gradient decent applied to LSTM is usually slower than necessary when applied to time service because they depend on instantaneous estimations of the gradient [13]. Kalman filter overcomes this limitation. Thus, [13] combined Kalman filter with the LSTM architecture, resulting in improving upon the original decent learning algorithm marking LSTM achieve even faster convergence and much better performance.

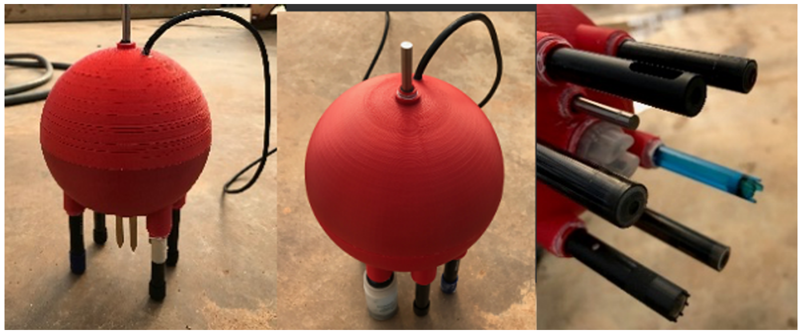
For body joint localization, camera pose estimation, and object tracking, one-shot pose estimation is typically noisy; temporal filters have been widely utilized for regularization. Kalman filters are often applied under the assumptions of constant velocity or constant acceleration. However, LSTM Kalman filter as a new architecture was proposed to gain the benefits of learning with less data [14]. In [14], the proposed estimation model learns to predict the uncertainty of initial prediction and incoming measurement, and the new architecture outperforms both Kalman filters with different transition models and LSTM.

Yu and Kim proposed an LSTM anomaly filter [10] performing better and detecting anomalies more effectively than can be achieved with other statistical filters. Anomaly detection is an approach that can be used to profile the normal runtime behavior of computer programs and thus to detect intrusions and errors as anomalous deviations from the observed normal baseline. However, normal but unobserved behavior can trigger false positives. The LSTM anomaly filter detects anomalies with zero false positives when filtering noisy behavior observations in an unsupervised manner.

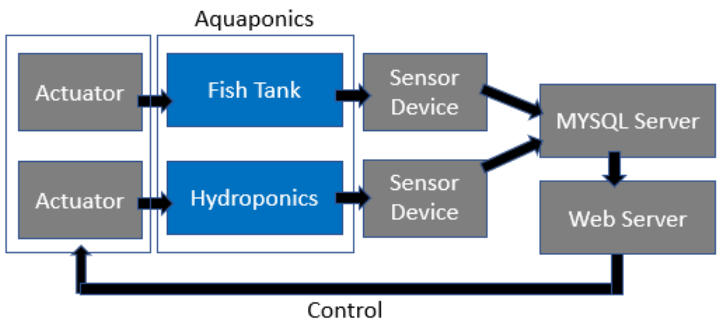
Kim et al. proposed the use of an LSTM filter to suppress noise and compared it with a moving average and Kalman filter, utilizing ammonium data [11]. Our research is an extension of [11] to minimize noise in agriculture sensors.

3 LSTM-KF IN AQUAPONICS

We have developed two sensor devices, including one for aquaculture and one for hydroponics. The aquaponics system has been controlled based on the data collected from these devices for sustainable agriculture automation. The major goal is to develop aquaponics automation technology that will revolutionize the sustainable production of fresh natural foods in and/or near urban centers in



(a) Sensor Devices



(b) Overal Achitecture

Figure 1: Aquaponics System

the US. The secondary goal is to determine how to apply this automation technology for use by a broad spectrum of sustainable food production sectors, including aquaculture, hydroponics, and traditional farming. This automation technology has been designed to maximize sustainable food production at minimum cost by addressing two of the most cost-intensive challenges currently faced by this sector: (1) the development of a high-quality labor force and prevention of loss due to human errors, and (2) continuous application of up-to-date science and knowledge. Figure 1(a) includes photographs of the sensor devices for use in agriculture automation. Two sensor devices containing *RaspberryPi* and agriculture sensors have been installed and are currently used to collect data from the aquaponics system. The sensor devices managed by Cloud-based IoT services generate data for every minute. A web server controls actuators by filtering the data as illustrated in Figure 1(b).

The aquaponics automation system consists of several components including, for example, the capacity to turn on the water heater in the fish tanks when the temperature goes below a lower threshold and likewise, the capacity to turn the heaters off when the temperature goes above an upper threshold. Other examples include the ability to divert water flow from the fish tanks to the vegetable beds when the water level or root moisture is below a threshold value and to redirect the water pump so that it moves water between the fish tank and the microbial chamber when the ammonia level is above a permissible threshold. To minimize false alerts in the threshold-based agriculture automation, how much the noise of the data stream from sensors is suppressed becomes the main research challenge. In this paper, three approaches are considered – Kalman, LSTM, and LSTM-KF filters.

The state vector for the Kalman filter (KF) is represented by x_i and y_i represents unobserved data. The forms of this filter can be written as follow: x_{i+1}=A_i x_i+B_i μ_i+G_i w_i and y_i=H_i x_i+v_i. x_i represents the system state vector, y_i represents the system observation vector, and μ_i represents the system control vector. A_i shows the transition matrix, H_i shows the observation matrix, B_i and G_i are dimensional matrices. w_i and v_i represent zero-mean, white noise error terms.

An LSTM unit consisting of a self-connected memory cell with multiplicative gates is shown in Figure 2. As a special recurrent neural network (RNN) with an input, hidden and output layers, LSTM has been utilized for long-range dependencies. The hidden layer of LSTM at time t, the output – $c^{(t-1,l)}$ and $h^{(t-1,l)}$ of the previous layer at $t-1$ come in the layer at t as inputs. LSTM controls a cell status $c^{(t-1,l)}$ that indicates an accumulated state information. The cell state is updated or cleared by several operations. If this state is cleared, the past cell status is forgotten by $f^{(t,l)}$. If updated, $c^{(t,l)}$ – one of the outputs at t will be propagated to the final state. The cell state is prevented from vanishing or exploding gradient, which is a problem of the traditional RNN, resulting in more learning capacity.

LSTM-KF is an approach for combining the strengths of LSTM networks and KF for time series prediction. The approach is motivated by the fact that both LSTM networks and the KF capture

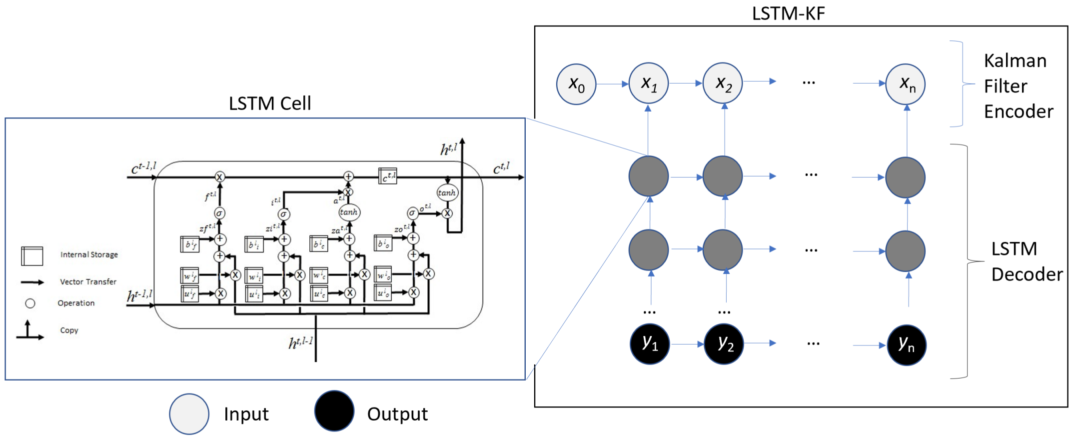


Figure 2: Schematic of LSTM-KF

long-term dependencies in time series data. However, LSTM networks capture complex non-linear dependencies, while the KF is limited to linear dependencies. The LSTM-KF approach combines the two methods by using the LSTM network to learn the non-linear dependencies in the data and using the KF to encode the input of the LSTM network as shown in Figure 2.

4 EVALUATION

KF [6] is a widely used, studied, and developed filter, which occupies a dominant position in the field of noise suppression. In this section, we compare LSTM-KF with LSTM and KF. For fair comparison, the same period of sample data streams in our sensor devices were used.

Figure 3 illustrates four ammonium charts. Ammonia plays a significant role in an aquaponics system. Fishs produce waste that is full of ammonia. Bacteria convert them into nitrites and then nitrates are necessary for plant growth. Table 1 shows the comparison on mean square error for Kalman, LSTM and LSTM-KF. Figure 3(a) shows the normal case of ammonium. The distribution depicted is uniform ranging between 0.05ppm and 0.10ppm. Ammonia water drains to a bacterial chamber when the level of ammonium reaches a certain level. As the plants absorb the nutrients, the water is purified for the fish and then recycled to the fish tank as illustrated in Figure 1(b). Figures 3(b) and 3(d) show ammonium charts at this moment. Even if Figures 3(a) and 3(c) present a normal case, the values of ammonium are highly fluctuated. A value may touch the level, resulting in supplying insufficient ammonium. Due to unbalanced nutrition, the growth of plants may be limited. Uncertainties arising from the varied movements of fish in a tank, such as feeding and growth, are the primary cause of fluctuations. LSTM and LSTM-KF models are utilized to capture the relationships between fish movements. These models aim to provide a more accurate and comprehensive understanding of the underlying dynamics of fish tanks.

To show the effectiveness of LSTM-KF, Table 1 presents the comparison of the mean square error.

Table 1: Comparison on Mean Square Error of Ammonium

Filters	Kalman	LSTM	LSTM-KF
MSE	0.0015982	0.000999943	0.000080789592
RMSE	0.0399775	0.0316219	0.0089883

In Figures 3, LSTM-KF (in green color) outperforms both LSTM (blue color) and Kalman filters (red color). The graphs show that LSTM-KF minimizes noise as it has the minimum fluctuation.

5 CONCLUSION

We proposed a noise suppression filter - LSTM combined with Kalman filter (LSTM-KF) filter installed in agriculture sensors and compared it with traditional filtering algorithms - LSTM and Kalman filters. The LSTM-KF is applied for large-scale aquaponics automation, improving sustainable food production. The accuracy of sensors and actuators' interactions is essential for knowledge- based automation. LSTM-KF minimizes noise of data from agriculture sensors, resulting in precisely controlling the actuators.

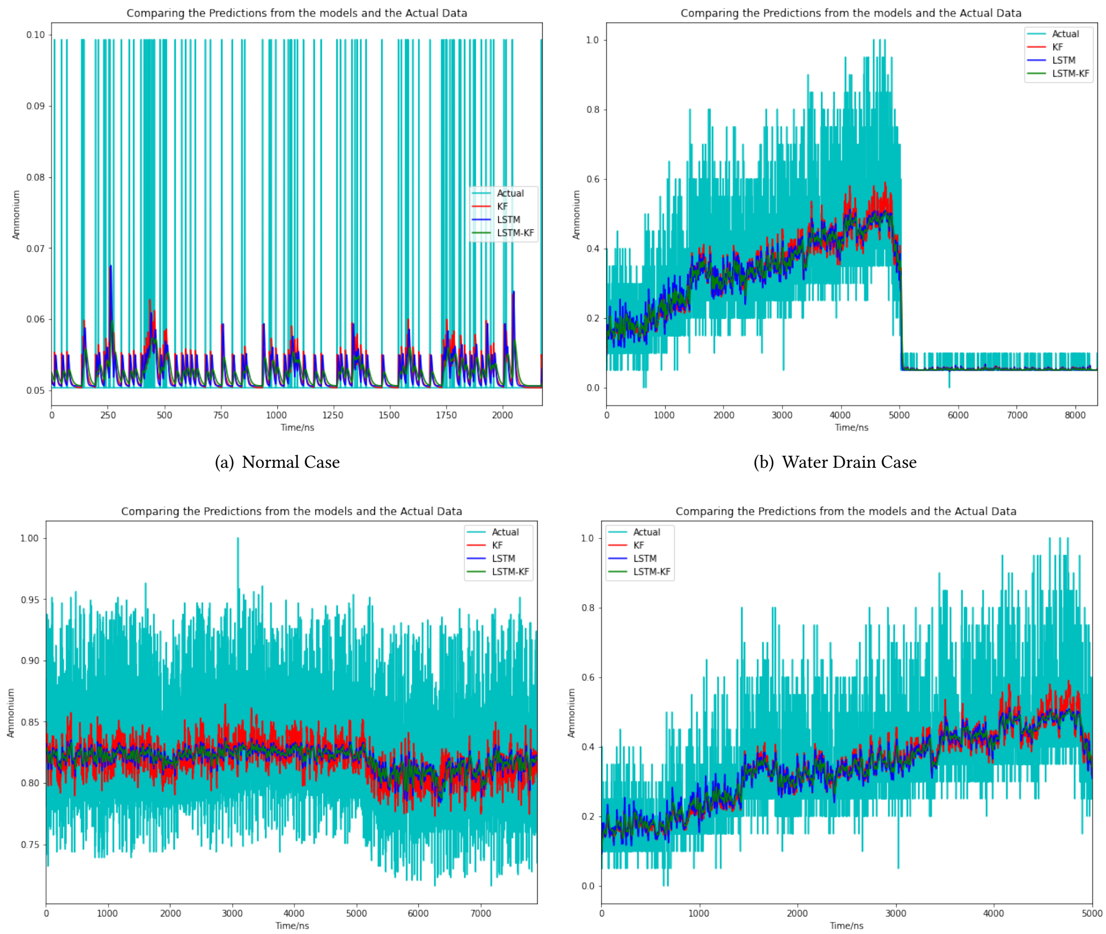
One potential future direction is the integration of a Transformer model, an attention-based neural network (ANN), with LSTM to enable the attention mechanism to consider all hidden states from each encoder node at every time step and make informed predictions. However, the large dataset required to train an ANN poses a challenge in implementing it on microcomputers. In light of this, we plan to explore the use of a compact Transformer model in our sensor devices as a means of improving the performance and compactness of noise suppression in future work.

ACKNOWLEDGMENTS

This work has been supported by US National Science Foundation CISE-MSI (RCBP-ED: CNS: Data Science and Engineering for Agriculture Automation) under grant 2131269.

REFERENCES

[1] Sabine O'Hara, and Etienne C. Toussaint, "Food access in crisis: Food security and COVID-19," Ecological Economics, vol.180, 2021



(a) Normal Case

(b) Water Drain Case

(c) Normal Case

(d) Water Supply Case

Figure 3: Ammonium Charts (ppm)

[2] Sabine O'Hara and Maros Ivanic, "Food Security and Lifestyle Vulnerabilities as Systemic Influencers of COVID-19 Survivability," EMedical Research Archives, No. 8 vol.10, 2022

[3] Canning, Patrick N, "Energy use in the US food system," No. 94, Diane Publishing, 2010

[4] Greenwood, N, "Food Carbon Footprint Calculator–Carbon Emissions," 2006

[5] Weber, Christopher L and Matthews, H Scott, "Food-miles and the relative climate impacts of food choices in the United States," ACS Publications, 2008

[6] Meinhold, Richard J and Singpurwalla, Nozer D, "Understanding the Kalman filter," The American Statistician, No. 2, Vol. 37, Taylor & Francis, 1983

[7] Love, David C and Fry, Jillian P and Li, Ximin and Hill, Elizabeth S and Genello, Laura and Semmens, Ken and Thompson, Richard E, "Commercial aquaponics production and profitability: Findings from an international survey," 2018 6th IEEE international conference on wireless for space and extreme environments (WISEE), 2018

[8] Yael Edan and Shufeng Han and Naoshi Kondo, "Automation in Agriculture," Springer Handbook of Automation, 2009

[9] Yaqi CUI and You HE and Tiantian TANG and Yu LIU, "A new target tracking filter based on deep learning," Chinese Journal of Aeronautics, No. 5, Vol 35, 2022

[10] Yu, Byunggu and Kim, Junwhan, "sing a Neural Network to Detect Anomalies Given an N-gram Profile," Cyber Security Cryptography and Machine Learning, 2021

[11] Junwhan Kim and Byunggu Yu and Sabine O'Hara, "LSTM Filter for Smart Agriculture," The 13th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN) / The 12th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH-2022) / Affiliated Workshops, 2022

[12] Ayaz, Muhammad and Ammad-Uddin, Mohammad and Sharif, Zubair and Mansour, Ali and Aggoune, El-Hadi M., "Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk," IEEE Access, Vol 7, 2019

[13] Pérez-Ortiz, Juan Antonio and Gers, Felix A. and Eck, Douglas and Schmidhuber, Jürgen, "Kalman Filters Improve LSTM Network Performance in Problems Unsolvable by Traditional Recurrent Nets," Neural Networks, Elsevier, No. 2, Vol. 16, 2003

[14] Coskun, Huseyin and Achilles, Felix and DiPietro, Robert and Navab, Nassir and Tombari, Federico, "Long Short-Term Memory Kalman Filters:Recurrent Neural Estimators for Pose Regularization, " arXiv, https://arxiv.org/abs/1708.01885, 2017