Learning Estimates At The Edge Using Intermittent And Aged Measurement Updates

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Abstract—Cyber Physical Systems (CPS) applications have agents that actuate in their local vicinity, while requiring measurements that capture the state of their larger environment to make actuation choices. These measurements are made by sensors communicated over a network as update packets. Network resource constraints dictate that updates arrive at an agent intermittently and be aged on their arrival. This can be alleviated by providing an agent with a fast enough rate of estimates of the measurements.

Often works on estimation assume knowledge of the dynamic model of the system being measured. However, as CPS applications become pervasive, such information may not be available in practice. In this work, we propose a novel deep neural network architecture that leverages Long Short Term Memory (LSTM) networks to learn estimates in a model-free setting using only updates received over the network. We detail an online algorithm that enables training of our architecture.

The architecture is shown to provide good estimates of measurements of both a linear and a non-linear dynamic system. It learns good estimates even when the learning proceeds over a generic network setting in which the distributions that govern the rate and age of received measurements may change significantly over time. We demonstrate the efficacy of the architecture by comparing it with the baselines of the Time-varying Kalman Filter and the Unscented Kalman Filter. The architecture enables empirical insights with regards to maintaining the ages of updates at the estimator, which are used by it and also the baselines.

I. INTRODUCTION

CPS applications, for example vehicle-to-everything (V2X) and public safety, are amongst the key use cases of next generation networks. These applications typically have one or more agents actuate in their local physical environment while obtaining measurements of the state of their larger environment and information about the controls (actuation) chosen by other agents, which an agent may not be able to sense individually, from other agents or sensors that are a part of the infrastructure, in the form of update packets over a communications network. For example, an autonomous vehicle may want to track the states (typically, 2-D positions and velocities) of other actors that share the road, not all of whom may be visible to the vehicle’s sensors.

While agents adapt their controls and sensors make measurements that capture the state of the environment at a fast enough rate, an agent may not receive update packets at a similar rate, given network resource constraints. Update packets at an agent will typically be intermittent and aged when received. To compensate for the intermittent measurements an agent could calculate estimates of the measurements using the history of update packets received by it.

While the problem of estimation has been studied extensively, typically the knowledge of the dynamic model of the environment or system being measured is assumed. Given the expected burgeoning of autonomous systems and their resulting interaction, assuming availability of such model information may not be practical. This together with the recent increase in compute available at edge devices, motivates us to investigate a model-free data driven approach to estimation, which will execute on an agent or an edge-server connected to the agent via a very low latency access link.

We will refer to the agent calculating the estimates as the edge-estimator and the entity whose state measurements or controls are received in updates as the target-agent. Our specific contributions include:

1) We propose a novel Deep Neural Network based approximation architecture at the edge-estimator, which uses the LSTM cell together with fully-connected layers, to learn estimates of measurements of the target-agent’s state.

2) We propose a learning algorithm that uses the experience replay buffer, which is commonly used in Deep Reinforcement Learning, in our problem setting. This enables us to train the proposed architecture using updates about the target received over the network, which may be time correlated.

3) We demonstrate empirically that the architecture doesn’t need to be trained separately for specific network instances. In fact, it may be trained over a generic network with time-varying network parameters. This enables its use in the real-world where network settings may not be known upfront.

4) We show that the architecture outperforms the Time Varying Kalman Filter (TVKF) and the Unscented Kalman Filter (UKF), respectively for a linear and nonlinear dynamic system, for when both the measurements of the state and the associated controls are communicated over the network. Even when current controls are assumed known at the estimator, the architecture performs almost as well as the TVKF, which is the optimal estimator for a linear system, and the UKF.

5) We demonstrate the efficacy of the architecture when the estimates of age of measurements and controls at the estimator are noisy, say because of lack of time synchronization.
Related Works: There are works [1]–[3] within the realm of networked control systems that consider the problem of optimal estimation and control when sensors communicate measurements to estimators over a communications network. These works assume knowledge of the dynamical model. Often assumptions are made regarding the model of packet delay and dropout over the communication network. The sensors, estimators, and controllers are cognizant of the underlying network and adapt to it to optimize the control utility while ensuring stability.

In [4], the time-varying Kalman filter with an infinite time buffer is shown to be the optimal estimator for a linear system in the presence of intermittent and aged measurements and known controls. Estimation using the unscented Kalman filter in presence of intermittent (but not aged) measurements is considered in [5].

There is a large body of works under the umbrella of deep reinforcement learning [6] that learn policies for agents in a model-free setting in a data driven manner. However, none to our knowledge address the setting of intermittent and aged measurements over a network.

II. SYSTEM MODEL

We describe the dynamic system that governs the state evolution of the target-agent and measurements of the same. We also describe the network model that governs the communication of measurements of the state to the edge-estimator.

We assume a discrete-time dynamic system wherein time is slotted with slots indexed by 1, 2, . . . . Slot k begins at time \( t_k \). The duration of any slot is assumed to be a constant \( h \), where \( 1/h \) is the sampling rate, which depends on the dynamic system (target) of interest. We have \( t_{k+1} - t_k = h \), for all slots \( k \). A dynamic system is described by its state evolution and observation equations given by, respectively,

\[
x_{k+1} = f_k(x_k, u_k, w_k), \quad (1a)
\]

\[
y_k = g_k(x_k, v_k). \quad (1b)
\]

Here \( x_k = x(t_k) \) is the state vector \( x \) of the dynamic system at \( t_k \), \( u_k = u(t_k) \) is the vector of controls applied at \( t_k \), \( w_k = w(t_k) \) is the vector input disturbance at \( t_k \), \( y_k = y(t_k) \) is the measurement vector \( y \) corresponding to the state of the system at \( t_k \), and \( v_k \) introduces error in the measurement. The vector function \( f_k() \) governs the state evolution, while \( g_k() \) maps the state to a measurement.

The estimator computes estimates of the measurements of the target at discrete time instants \( t_{i,1}, t_{i,2}, \ldots \). Let \( \hat{y}(t) \) be the estimate of measurement \( y \) at \( t \). The estimator calculates \( \hat{y}(t_k) \) using the measurements and controls it has received via update packets at times \( t \leq t_k \). Specifically, at \( t_k \), the estimator first checks if it has received a more recent measurement and/or control since \( t_{k-1} \) and then uses all its received measurements and controls to calculate \( \hat{y}(t_k) \). Further, let the slot length of any slot \( k \) at the estimator be a constant \( h_e = t_k - t_{k-1} \). We will refer to \( 1/h_e \) as the estimation rate.

Denote the measurement in the \( i \)th element of measurement vector \( y \) as \( y[i] \). Let \( y[i](t_k) \) be the value it takes at \( t_k \). That is \( y[i](t_k) \) is the \( i \)th element of \( y_k \). Note that \( t_k \) is the generation timestamp of \( y[i](t_k) \). Similarly, the timestamp of control \( u[i](t_k) \) is \( t_k \).

The measurements and controls are received by the estimator over a communications network. As a result, at any time \( t \), it will have access to aged measurements and controls that capture an older time snapshot in the evolution of the dynamic system. Let \( z \) denote any measurement or control. For example, \( z \) could be \( y[i] \). Let \( U_i(z) \) be the most recent generation timestamp of the update \( z \) at the estimator at time \( t \). The age of update \( z \) at the estimator at \( t \) is

\[
\Delta_u(t) = t - U_i(z). \quad (2)
\]

To exemplify, suppose the most recent generation timestamp of \( y[i] \) at the estimator, at time \( t \), is \( t' \). That is amongst all updates of \( y[i] \), which the estimator has received so far over the network, the one with a timestamp of generation closest to \( t \) is \( y[i](t') \). Clearly, \( t \geq t' \). The age \( \Delta_y[i](t) \) of \( y[i] \) is

\[
\Delta_y[i](t) = t - t'.
\]

Note that \( \Delta_u(t) \) at the estimator increases at unit rate in the absence of an update with a more recent timestamp than already at the estimator. Further, it is reset to a smaller value at time \( t \) in case an update with a more recent than available timestamp is received at \( t \). Specifically, \( \Delta_u(t) \) is reset to the time elapsed between the generation of the received update and its being received at \( t \).

We now describe the communications network. We assume that measurements \( y_k \) are encapsulated as an update packet that is sent over the network by the sensor making the measurement to the estimator. Our network model must capture the fact that the effective source rate at which measurements are transmitted over the network may be much smaller than the sampling rate \( 1/h \). This could be because network resource constraints or energy constraints preclude scheduling of a measurement, a measurement is dropped by the network, say because of queuing and transmission. Also, a measurement that is delivered to the estimator will have suffered communication delays because of queuing and transmission.

In what follows, we will simulate the network by a discrete-time queue with an infinite buffer and a single server. A measurement \( y_k \) is communicated as an update packet with probability \( p \), which is the arrival rate of packets into the queue, independently of other measurements. Packets that enter the queue are serviced in a first-come-first-served manner and each packet spends a geometric \( (q) \) time in the server, independently of other packets. On completion of service, a packet arrives at the estimator and can be used for estimating the state of the target.

III. APPROXIMATION ARCHITECTURE

We propose a Long Short Term Memory (LSTM) [7] based approximation architecture (LSTM-AA), which is a Deep Neural Network, for the estimator to calculate estimates at time instants \( t_k \), \( k \in \{1, 2, \ldots \} \). An LSTM is a sequence model that maps a time sequence of inputs to an output sequence
and the ability to capture long range time dependencies of an output on an input sequence.

In our architecture, illustrated in Figure 1 at any $t \in \{t^1, t^2, \ldots\}$ the LSTM cell takes as input a vector of most recently received measurements and controls and their ages at the estimator. Let $\tilde{y}[i]$ and $\tilde{u}[j]$ respectively be the most recently received update corresponding to the measurement $y[i]$ and the control $u[j]$. Their ages at the estimator are respectively $\Delta y[i](t)$ and $\Delta u[j](t)$. Define $\bar{y}$ as the vector containing $\tilde{y}[i]$, where $i$ as before indexes the measurements in the measurement vector $y$. Similarly, define the vectors $\bar{u}$, $\Delta y$, and $\Delta u$. The input to the LSTM cell at $t$ is

$$I(t) = [\bar{y}(t-1) \ \bar{y}(t) \ \bar{u}(t) \ \Delta y(t) \ \Delta u(t)]'. \quad (3)$$

We pass the output $h(t)$ (also called the hidden state) of the LSTM cell as input to a fully-connected layer FC1 that is parameterized by the weight matrix $W_{FC1}$ and the bias vector $b_{FC1}$. The output of this layer is given by $o_{FC1}(t) = \text{ReLU}(W_{FC1}h(t) + b_{FC1})$, where $\text{ReLU}()$ is the Rectified Linear Unit and is a commonly used non-linear activation function.

The output $o_{FC1}(t)$ is input to another fully-connected layer FC2, which is parameterized by the weight matrix $W_{FC2}$ and the bias vector $b_{FC2}$. The output of the layer is the estimate $\hat{y}(t)$ and is calculated as $\hat{y}(t) = W_{FC2}o_{FC1}(t) + b_{FC2}$. This estimate is a part of the input to the LSTM cell at $t + 1$.

Note that the LSTM cell independently updates its cell state, its hidden state, the input, forget, cell and output gates, at every time $t$. Further, the cell contains its input-hidden and the hidden-hidden weights and biases that must be learnt together with $W_{FC1}$, $b_{FC1}$, $W_{FC2}$, and $b_{FC2}$. We skip the details (see [8]) specific to LSTM for clarity. Figure 1 illustrates our architecture rolled out over a couple of time steps.

Let the vector $\Theta$ comprise of all the weights and biases of our proposed architecture. Define the measurement residual as $\epsilon_{y}(\Theta) = y - \hat{y}(\Theta)$. The estimator would like to minimize the mean squared measurement residual $\|\epsilon_{y}(\Theta)\|^2$ with respect to $\Theta$, using measurements obtained over a certain time horizon $T$. The optimization problem is

$$\text{minimize}_{\Theta} \frac{1}{T} \sum_{t=1}^{T} \epsilon_{y}(t)(\Theta)' \epsilon_{y}(t)(\Theta), \quad (4)$$
in other ways. Howsoever the control may be chosen, the mechanism is assumed unknown to the estimator.

Any update packet that completes service is received by the estimator. Also, with probability \( p \), \( y(t) \) and \( u(t) \) are added to the network queue\(^1\).

The estimator stores its experience at \( t \). The experience includes the input \( I(t) \) to LSTM-AA and the ground-truth measurement \( y(t) \). It must be pointed out that the ground-truth is only needed while the estimator is in the process of learning a good weight vector \( \Theta \). Further, while we assume that the ground-truth is readily available, in practice the said ground-truth is only available if and when the measurement \( y(t) \) is received by the estimator over the communications network. Assuming that the latter is the case, the estimator must add the experience corresponding to the input \( I(t) \) if and when \( y(t) \) is received. While this would result in experiences being added to the replay memory at a slower rate than when the ground-truth is readily available, the algorithm stays unchanged.

In addition, at every time \( t \) (even if no new experience was added, as may happen in practice) the estimator calculates the average squared error over a randomly chosen mini-batch\(^2\) of experiences in the replay memory. Note that the calculation of error requires forward propagation\(^3\) using LSTM-AA. Specifically, for each experience we must input the corresponding \( I \) to LSTM-AA and obtain the \( \hat{y}(t) \). The error is then used to update \( \Theta \) using gradient descent. This requires calculation of gradient of the mean squared measurement residual cost function with respect to the weight vector \( \Theta \) (referred to as Backpropagation\(^4\)).

On the replay memory: The replay memory is often used to ensure that consecutive weight updates result from experiences that are independent of each other. Choosing experiences in the time sequence in which they occur would result in strongly correlated experiences updating the weight vector, which is detrimental to learning. The use of replay memory, when training a deep neural network, to break correlations is common (for example, see \([6]\)).

On Training and Testing LSTM-AA: In what follows, we will refer to the task of learning a weight vector using Algorithm\(^1\) as training. A trained LSTM-AA model is fully described by the learnt weight vector \( \Theta \) and the approximation architecture described in Section\(^II\). Testing a model involves using the trained model to calculate estimates \( \hat{y}(t) \), for all \( t \). Note that in practice the estimator could keep improving and adapting its estimates of \( \Theta \) while also simultaneously using the vector at any time \( t \) to calculate the estimate \( \hat{y}(t) \).

We used the Adam optimiser with learning parameter \( 10^{-4} \) and minibatch size of 256. We used a hidden layer of size 64 for both LSTM and the fully connected layers. To prevent the model from overfitting, we use a \( L2 \) weight decay of \( 10^{-3} \). Our replay memory is of size \( 2 \times 10^6 \).

V. Trained Models And Baselines

Real-world settings are likely to see a wide variety of dynamical systems and networks that enable communication of updates to estimators. We will focus on demonstrating the efficacy of LSTM-AA over a spectrum of key assumptions about dynamical systems and networks, with the goal of covering a diverse range of real-world possibilities. A system could have either linear or non-linear dynamics. Network between the target and the estimator could remain stationary. On the other hand, the target and the estimator may over time experience non-stationary network conditions. Last but not the least, a network may not be able to maintain timestamps to enable accurate calculation of ages at the estimator.

A choice of key assumptions will result in a distinct simulated world. We use Algorithm\(^1\) to separately train LSTM-AA on each chosen simulated world and then carry out testing of the trained models to compare LSTM-AA’s efficacy across the different worlds.

Dynamical Systems: We will train and test LSTM-AA on two dynamical systems. We consider a linear dynamical system that models an agent that moves in 2-dimensional space, wherein the motion is governed by Newtonian kinematics. This model for a target is often used in work on autonomous vehicle path planning. For example, see \([11, \text{Equation (11)}]\). Though we have an added process and observation noise with \( w, v \sim \mathcal{N}(0, 0.1) \). The estimator would like to estimate the current position and velocity of the target. We also consider a Cartpole, which is a non-linear dynamical system that has a pole attached to a cart. The estimator would like to estimate the position and angular velocity of the pole. The Cartpole is often used to demonstrate the efficacy of deep reinforcement learning algorithms with respect to balancing the unstable pole on the cart\(^12\).

Communication Networks: We consider example networks

![Fig. 2: Average age as a function of utilization for \( q = 0.3, 0.5 \).](image)

with fixed \( p \) and \( q \) for all time and also a network in which \( p \) and \( q \) change over time. For when the network parameters are time-invariant, we choose \( p = 0.01, 0.1, 0.297 \) for \( q = 0.3 \), and \( p = 0.01, 0.3, 0.499 \) for \( q = 0.5 \). The choices of \( p \) for each \( q \) are motivated by Figure\(^2\) that shows how the average age of updates varies at the estimator as a function of \( p \) for \( q = 0.3, 0.5 \). As is seen in the figure, the average age is high for both \( p = 0.01 \) and \( p = 0.297 \) when \( q = 0.3 \). However, as

\(^1\)As described in Section\(^II\), every measurement in \( y(t) \) and every control in \( u(t) \) can be queued as separate update packets. However, for simplicity, in this work we assume that all information that is queued at any time \( t \) is queued as one update packet.

\(^2\)Referred to as a mini-batch as it is typically a small subset of all experiences in the replay memory.
has now been shown to hold true for a wide range of network settings [13], the high age at \( p = 0.297 \) is explained by a low rate \( p \) of sending of updates, relative to \( q \), over the network. A small \( p \) with respect to \( q \) results in low utilization of the queue server by the update packets. A packet that arrives to the queue suffers low delays before completing service. While this is good to keep age low, the age at the estimator is high because the server receives updates infrequently.

However, the reason for the high age at \( p = 0.297 \) is that the rate of sending updates is very high. The high rate results in high utilization of the server and the updates that arrive at the queue experience large queuing delays because of congestion. While the estimator now receives updates at a high frequency, the updates are aged because of the delay they have suffered in the network. The high average ages when \( p = 0.01, 0.499 \) for \( q = 0.5 \) can be explained similarly.

So for both \( q = 0.3, 0.5 \), we choose high age settings, one of which is due to infrequently sent updates (low rate of updates) and the other because of congestion (high delay) in the network. The remaining fixed network settings include \( p = 0.1, q = 0.3 \) and \( p = 0.3, q = 0.5 \). These settings result in close to minimum average age.

Last but not the least, note that the probability \( q \) implies that the network on an average allocates its resources (service facility) a fraction \( 1/q \) of the time to target’s updates that require transmission. The fraction captures the fact that network resources are shared amongst multiple traffic flows.

**Time-varying network parameters:** When training the model for this setting we choose \( p \) and \( q \) uniformly and randomly at the beginning of each episode, independently of the choices of \( p \) and \( q \) made at the beginning of other episodes. We choose \( q \in [0.007, 1] \) and \( p \in [0.0007, q] \). We sample from a very wide a range of network settings. The time-varying \( p \) and \( q \) models a non-stationary network setting.

**Estimating Age of an Update at the Estimator:** The input to LSTM-AA, as described in [3], includes the age \( \Delta u(t) \) for updates \( u \), which could be either measurements or controls. Reception of a more recent update resets the age \( \Delta u(t) \) of the update at the estimator to the time spent by the update between generation and being received at the estimator. In practice, getting an accurate estimate of this time requires the source of the update and the estimator to be time-synchronized. This is hardly ever perfect. In fact, often such synchronization is not assumed. Instead the delay is estimated using surrogates like the round-trip-time (between the source and the estimator). In general, as a result, the age estimates on receiving a more recent update are noisy.

We will train models separately under the two assumptions of access to true age at the estimator and the absence of age vectors in the input [3]. We test the model trained using true age using age inputs to LSTM-AA that are noisy. Specifically, the estimated age on reset is assumed to be scaled by a continuous uniform random variable that takes values in \((0, 2)\). We add a standard normal with zero mean and standard deviation equal to 10% of the true age to the scaled value.

**Baselines:** We compare the testing performance of our trained models with that obtained when using the Time-Varying Kalman Filter (TVKF) with infinite time buffer [4] for the linear dynamic system and the Unscented Kalman Filter [5] for the non-linear dynamic system. Note that both the TVKF and the UKF assume knowledge of the dynamic system model.

The TVKF is chosen as a baseline as it is known to be the optimal estimator when the controls is known to the estimator at all times. As in our case, the controls are also obtained over the network, we assume that the TVKF keeps using the last known control till a more recent packet containing controls is received over the network.

We also train LSTM-AA under the assumption that the current controls are always known to the estimator. This gives us a good sense of the efficacy of our training algorithm, as for when controls are known the TVKF is the optimal estimator.

For a non-linear dynamic system, we were only able to find a UKF implementation [5] that works with intermittent updates. However, an update when received is current (fresh, age 0). We modify the UKF implementation as (i) upon no new update we propagate the prior state estimates and error covariance according to the system dynamic model and set the posterior of the state and error covariance same as the prior, and (ii) when a new update packet arrives, we determine the timestamp of the received information and update the corresponding posterior information, followed by the prior and posterior propagation of the state and error covariance.

**VI. RESULTS**

![Fig. 3: Comparison of LSTM-AA and (a) the TVKF and (b) the UKF, for when controls are known.](image)

![Fig. 4: Controls are communicated over the network for \( q = 0.3 \). (a) Linear system (b) Nonlinear. Results for \( q = 0.5 \) are not shown but look similar.](image)

We describe the empirical takeaways obtained from training and testing our proposed architecture on our simulated worlds. We quantify the estimation performance of LSTM-AA and
Baseline assuming known current control: We begin by showing a comparison of LSTM-AA for when the current control is always known. For this setting, the baseline algorithms of TVKF and UKF are expected to do well. In fact TVKF is the optimal estimator for a linear system. Figure 5a compares the estimation error obtained using LSTM-AA and the TVKF for the linear dynamic system. The algorithms are compared for when \( q = 0.3 \) and \( p \) takes values of 0.01 (Low Rate), 0.1 (close to Age Optimal Rate), and 0.297 (High Delay). LSTM-AA was trained and tested separately for each value of \( p \). Both training and testing were done over 200 episodes. As is seen from the figure, LSTM-AA performs almost as well as the TVKF. Figure 5b compares LSTM-AA and UKF. LSTM-AA performs well in comparison to the UKF.

How does LSTM-AA do when the control information is also communicated over the network?: Figure 6 compares LSTM-AA trained with and without the age inputs \( \Delta_u \) and \( \Delta_y \). Figure 6a is for the linear dynamic system and also shows the performance of the TVKF. Figure 6b is for the nonlinear system and shows the performance of the UKF. LSTM-AA for both when age is input and not was trained and tested for 300 episodes for each \( p, q \). It is clear that LSTM-AA with the age inputs does the best and in fact a lot better than the TVKF and the UKF. LSTM-AA without the age inputs performs fairly well when \( p \) is set close to the age optimal rate but suffers otherwise. Keeping the age inputs clearly benefits estimation.

Further see Figure 5 for the impact of noisy age estimates at the estimator on its performance. Note that LSTM-AA was trained as above with true age values at its input. Noisy age estimates were only provided when testing. The estimation performance of LSTM-AA is not very impacted. The TVKF’s estimation error shows a significant increase, however.

Does LSTM-AA train well over a non-stationary network? Or do we need to train it separately for every specific network setting of interest?: To have to train LSTM-AA separately for specific network settings would make it impractical. Often, the network parameters aren’t known and change over time. Figure 6 compares the testing performance of LSTM-AA trained over a time-varying network with the testing performance of LSTM-AA trained for the same network parameters that are used for testing. Figures 6a and 6b show that the testing performance of the model trained using a time-varying network is in fact almost as good as that trained for the fixed network setting. The estimator doesn’t need to train different LSTM-AA models for different networks. For Figure 6a the testing was done for \( q = 0.3 \) and a linear system. In the other figure, the system is nonlinear and \( q = 0.5 \).

VII. CONCLUSION

We proposed a deep neural network model to learn estimates of state measurements in a model-free setting using intermittent and aged state measurements received over the network. We demonstrated the efficacy of the model by comparing it with the baselines of the TVKF and the UKF for various network setting and for both a linear and a nonlinear system.

REFERENCES

[1] J. P. Hespanha, P. Naghshtabrizi, and Y. Xi, “A survey of recent results in networked control systems,” Proceedings of the IEEE, vol. 95, no. 1, pp. 138–162, 2007.
[2] L. Schenato, B. Sinopoli, M. Franceschetti, K. Poolla, and S. S. Sastry, “Foundations of control and estimation over lossy networks,” Proceedings of the IEEE, vol. 95, no. 1, pp. 163–187, 2007.
[3] P. Park, S. C. Ergen, C. Fischione, C. Lu, and K. H. Johansson, “Wireless network design for control systems: A survey,” IEEE Communications Surveys & Tutorials, vol. 20, no. 2, pp. 978–1013, 2017.
[4] L. Schenato, “Optimal estimation in networked control systems subject to random delay and packet drop,” IEEE transactions on automatic control, vol. 53, no. 5, pp. 1311–1317, 2008.
[5] L. Li and Y. Xia, “Stochastic stability of the unscented kalman filter with intermittent observations,” Automatica, vol. 48, no. 3, pp. 978–981, 2012.
[6] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller, “Playing atari with deep reinforcement learning,” arXiv preprint arXiv:1312.5602, 2013.
[7] S. Kaul, R. Yates, and M. Gruteser, “Real-Time Status: How Often Should One Update?” in Proc. IEEE INFOCOM Mini Conference, 2012.
[8] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.
[9] A. F. Agarap, “Deep learning using rectified linear units (relu),” arXiv preprint arXiv:1803.08375, 2018.
[10] R. F. Stengel, Optimal control and estimation. Courier Corporation, 1994.
[11] C. Hubmann, J. Schulz, M. Becker, D. Althoff, and C. Stiller, “Automated driving in uncertain environments: Planning with interaction and uncertain maneuver prediction,” IEEE Transactions on Intelligent Vehicles, vol. 3, no. 1, pp. 5–17, 2018.
[12] G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba, “Openai gym,” arXiv preprint arXiv:1606.01540, 2016.
[13] R. D. Yates, Y. Sun, D. R. Brown, S. K. Kaul, E. Modiano, and S. Ulukus, “Age of information: An introduction and survey,” IEEE Journal on Selected Areas in Communications, vol. 39, no. 5, pp. 1183–1210, 2021.