UAV detection based on wireless communication link via CSI autocorrelation function

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ABSTRACT

With the increasing popularity of unmanned aerial vehicles (UAVs), UAV detection technology has received increasing attention to address security threats. For broad deployment of UAV detection, it is more feasible to perform UAV detection based on existing communication networks than radars. This paper proposes a UAV detection method based on a wireless communication link via a channel state information (CSI) autocorrelation function. The algorithm can be executed in parallel with communication in existing transceivers as no additional signal design requirements and hardware requirements are needed but the CSI, which can be obtained with channel estimation in communication systems. Through experiments, the UAV is successfully detected based on the method proposed in this paper, which verifies its effectiveness.

Keywords: UAV detection, channel state information, integrated communication and sensing

1. INTRODUCTION

With the rapid development of technology, unmanned aerial vehicles (UAVs) have been increasingly widely used in civilian applications. However, the popularity of UAVs has also caused security problems[1]. After the UAV incident at Gatwick Airport in London, UK, in 2018[2], UAVs have come to be regarded as a potential threat to aviation safety by the public. Collision accidents of runaway UAVs have also been repeatedly reported. In addition, some incidents are even hostile in nature, such as illegal investigation or self-explosive destruction.

Because of the hidden danger posed by UAVs, UAV detection technology has received increasing attention. The radar method is still the best UAV detection method in terms of early warning capabilities[3-5]. However, because radar relies on the Doppler principle for target tracking, the detection effect for a hovering UAV is limited. More importantly, the cost of radar deployment is too high for widespread use. Optical detection and acoustic detection are also important methods that require only a suitable arrangement of sensors. The former achieves early warning by identifying UAV targets in real-time images, which has the advantage of intuitive target recognition but the disadvantages of being strongly affected by weather and offering limited dynamic adaptability[6-8]. The latter relies on acoustic sensors to obtain sound signals and compare them against the voiceprint information of a UAV motor and rotor under working conditions in an audio library to identify UAVs[7, 9]. However, existing research on acoustic detection has shown that its detection distance and effect are limited. In addition, spectral detection is an important means of UAV detection[10-13]. Spectral detection can be used to detect a UAV and even identify its brand and model by intercepting wireless signals for flight control and image transmission from the UAV, extracting signal characteristics such as frequency and bandwidth, and comparing them against a feature library. Spectral detection can be implemented with only a detection receiver; however, some a priori information on the working frequency bands of UAVs is necessary.

Considering the shortcomings of the above methods, this paper proposes a method to detect an intruding UAV by calculating an autocorrelation function of the channel state information (CSI). This method is based on the influence of a UAV on the channel environment and has some similarities with passive radar. However, because the Doppler phenomenon caused by small UAV is difficult to monitor[14], passive radar method has higher requirements for transceiver equipment. In contrast, the proposed method can be executed in parallel with communication in conventional single-antenna transceivers. Therefore, this method can be regarded as having very low equipment cost and can be widely

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deployed, which is more convenient to deal with small UAVs in urban areas. To the best of the authors' knowledge, no previous study has considered this method.

The main contributions of this work are summarized as follows:

- First, the channel models with and without UAV intrusion are given. The propagation channel is divided into local paths and an abnormal path. The abnormal path is caused by the presence of a UAV and can be employed for UAV detection.
- Then, we propose a UAV detection method based on a CSI autocorrelation function. The principle of this method is introduced in detail, and the specific steps are given.
- Finally, we report the experimental implementation of the proposed method, and the experimental results verify its feasibility.

2. SYSTEM MODEL

As illustrated in Figure 1, the propagation channel is divided into local paths and an abnormal path. The local paths represent the propagation paths in the local environment without the UAV, including the line-of-sight (LoS) path and the paths with reflection from local objects. The abnormal path is the reflection path introduced by the intrusion of the unauthorized UAV.

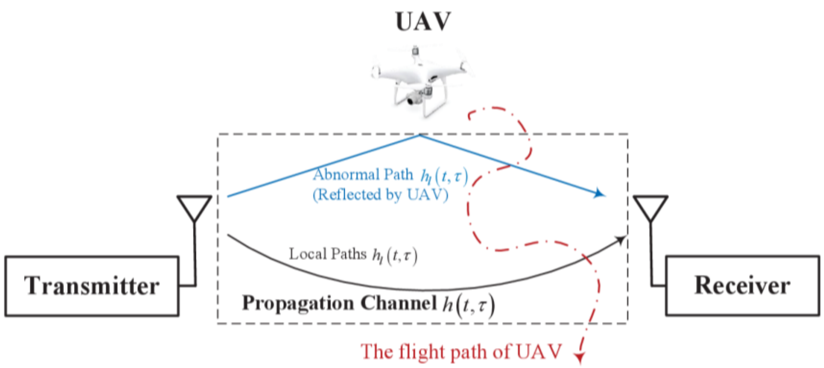

Figure 1. System Model. A scenario in which an unauthorized UAV intrudes into the propagation area of a set of common local transceivers. The local transceivers communicate with each other normally. At the same time, the receiver will sense the CSI and use it for UAV detection in parallel with communication.

- Without UAV intrusion. Considering that the propagation channel is varying in time and its response at time t is denoted by $h(t)$, the channel model without UAV intrusion can be expressed as

$$h(t,\tau)=h_l(t,\tau)=\sum_i h_i(t,\tau)\delta(\tau-\tau_i), i=1,\cdots,L \tag{1}$$

where $h_l(t)$ denotes the local paths, $\tau(i)$ is the delay on the k-th local path, and L is the number of local paths.

- With UAV intrusion. When the UAV flies into the propagation area of the local transceivers, an abnormal path is introduced by the reflection from the UAV, which is given by

$$h(t,\tau)= h_l(t,\tau)+h_a(t,\tau)\sum_i h_i(t,\tau)\delta(\tau-\tau_i)+h_{uav}(t)\delta(\tau-\tau_{uav}), i=1,\cdots,L \tag{2}$$

where $h_l(t,\tau)=h_{uav}(t)\delta(\tau-\tau_{uav})$ denotes the abnormal path introduced by the UAV, with complex gain $h_{uav}(t)$ and time delay τ_{uav}.

We can see from the above equations that there is a difference between the channels in the two scenarios, which can be employed for UAV detection. In the next section, the proposed UAV detection method based on a CSI autocorrelation function is described in detail.

3. METHOD

In this paper, we adopt a time-averaged autocorrelation function of the CSI to detect the channel anomaly caused by UAV intrusion in order to judge whether there is UAV intrusion. First, through channel estimation at the receiver, the estimated CSI at the n -th sample is obtained as

$$\hat{h}(n,m) = h(nT_s, mT_s) + e(n,m) \tag{3}$$

where T_s is the sampling period of the receiver, m is the discrete time delay, and $e(n)$ is the error of channel estimation. In this paper, we consider that $e(n,m)$ can be characterized as Gaussian noise that is independent of $h(t,\tau)$.

Then, the time-averaged autocorrelation function with delay d ($d \in \mathbb{N}$) of $\hat{h}(n)$ in the k -th window $n = (k-1)T_w, \ldots, kT_w - 1$ is calculated as

$$R_{\hat{h}}(k,d) = \frac{1}{T_w} \sum_{n=(k-1)T_w}^{kT_w-1} \sum_{m=-\infty}^{+\infty} \hat{h}(n,m)\hat{h}^*(n-d,m) \tag{4}$$

where T_w is the window length and $(\cdot)^*$ denotes the conjugate operation.

The results with and without UAV intrusion are different and are given as follows:

(1) Without UAV intrusion:

$$\begin{aligned} R_{\hat{h}}(k,d) &= \frac{1}{T_w} \sum_{n=(k-1)T_w}^{kT_w-1} \sum_{m=-\infty}^{+\infty} \hat{h}(n,m)\hat{h}^*(n-d,m) \\ &= \frac{1}{T_w} \sum_{n=(k-1)T_w}^{kT_w-1} \sum_{m=-\infty}^{+\infty} h_l(nT_s, mT_s) h_l^*\left[(n-d)T_s, mT_s\right] + \frac{1}{T_w} \sum_{n=(k-1)T_w}^{kT_w-1} \sum_{m=-\infty}^{+\infty} e(n)e^*(n-d) \\ &= R_{h_l}(k,d) + R_e(k,d) \end{aligned} \tag{5}$$

(2) With UAV intrusion:

$$\begin{aligned} R_{\hat{h}}(k,d) &= \frac{1}{T_w} \sum_{n=(k-1)T_w}^{kT_w-1} \sum_{m=-\infty}^{+\infty} \hat{h}(n,m)\hat{h}^*(n-d,m) \\ &= \frac{1}{T_w} \sum_{n=(k-1)T_w}^{kT_w-1} \sum_{m=-\infty}^{+\infty} \left[h_l(nT_s, mT_s) h_l^*\left[(n-d)T_s, mT_s\right] + h_a(nT_s, mT_s) h_a^*\left[(n-d)T_s, mT_s\right] \right] + R_e(k,d) \\ &= R_{h_l}(k,d) + R_{h_a}(k,d) + R_e(k,d) \end{aligned} \tag{6}$$

Algorithm 1. UAV detection based on a time-averaged autocorrelation function of the CSI

Require: $\hat{h}(n,m), d, \alpha, N_{Tol}$

Ensure: $Exist_{UAV}$

Initialize $k=1$, $N_{Exc}=0$, $N_{Les}=0$, $Exist_{UAV}=0$, $\lambda(0)=R_{\hat{h}}(0,d)=\sum_{m=-\infty}^{+\infty}\hat{h}(0,m)\hat{h}^{*}(-d,m)$

while $N_{Exc\_}>N_{Tol}$ or $N_{Les}>N_{Tol}$ do

Calculate the time-averaged autocorrelation function in the k -th window with an interval d $R_{\hat{h}}(k,d)$ using Equation (4);

if $R_{\hat{h}}(k,d)>\lambda(k-1)\}$ then

$N_{Exc}=N_{Exc}+1$;

$N_{Les}=0$;

else

$N_{Les}=N_{Les}+1$;

$N_{Exc}=0$;

end if

$\lambda(k)=\frac{\alpha\left(1-\alpha^{k}\right)}{1-\alpha^{k+1}}\lambda(k-1)+\frac{1-\alpha}{1-\alpha^{k+1}}R_{h}(k,d)$;

$k=k+1$;

end while

return $Exist_{UAV}=1$

From the above equations, it can be observed that the time-averaged autocorrelation function $R_{\hat{h}}(k,d)$ has one more term with UAV intrusion than it does without UAV intrusion. Under the assumption that the channel amplitude of the abnormal path introduced by the UAV is constant for the duration of the k -th window, the function can be simplified as

$$R_{h_a}(k,d)=\frac{1}{T_w}\sum_{n=(k-1)T_w}^{kT_w-1}\sum_{m=-\infty}^{+\infty}\hat{h}(n,m)h_a^{*}(n-d,m)=e^{j\phi}\left|h_{uav}\right|^{2} \tag{7}$$

where ϕ is the phase change caused by the movement of the UAV. Therefore, a threshold for UAV detection can be set based on the value of the time-averaged autocorrelation function without UAV intrusion. As the channel conditions without UAV intrusion are characterized by slow fading, the threshold after the k -th window is given by

$$\lambda(k)=\frac{1-\alpha}{1-\alpha^{k+1}}\sum_{i=0}^{k}\alpha^{k-i}R_h(i,d) \tag{8}$$

where $0<\alpha<1$ is the decay coefficient. In iterative form, the above equation can be written as

$$\lambda(k)=\frac{\alpha\left(1-\alpha^{k}\right)}{1-\alpha^{k+1}}\lambda(k-1)+\frac{1-\alpha}{1-\alpha^{k+1}}R_h(k,d) \tag{9}$$

To ensure robustness to small disturbances in the CSI, UAV intrusion is determined to have occurred only when N_{Tol} consecutive $R_{\hat{h}}(k,d)$ values are either all larger or all less than $\lambda(k-1)$, where N_{Tol} represents our tolerance to CSI disturbances. The specific steps of the proposed method are given in Algorithm 1.

4. EXPERIMENT AND RESULTS

In this section, we present experimental results obtained using the proposed algorithm. The experimental scene and equipment used are shown in Figure 2. Limited by the supporting hardware, detection was not performed in real time in the experiment. A signal generated by the PC was sent into the transmitting circuit board and transmitted via the transmitting antenna, using binary phase-shift keying (BPSK) modulation with a bandwidth of 9.6 MHz and a carrier frequency of 1.25 GHz. To simulate UAV intrusion, a UAV was controlled to fly from some distance away towards the antennas and then away. After propagation in the scene with and without UAV intrusion, the transmitted signal was received and collected by the PC for analysis using the proposed algorithm. In this experiment, a frame consisted of 200 symbols, the sampling frequency was 40 MHz, $d=1067$ samples, $\alpha=0.9$, and $N_{Tol}=3$.

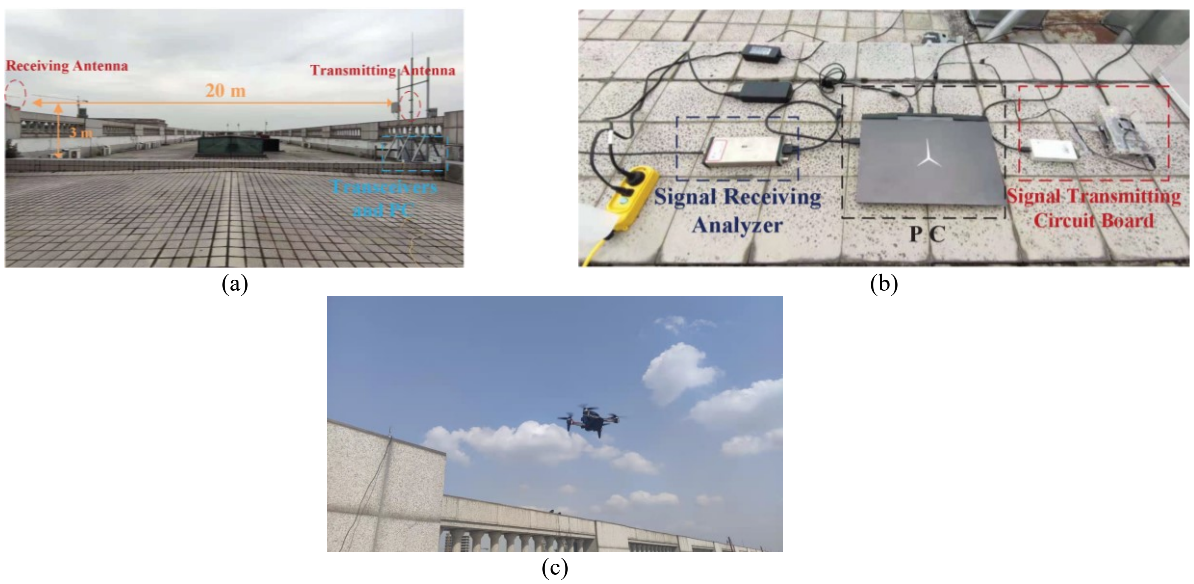

Figure 2. Diagrams of the experimental scene and equipments: (a) Experimental Scene; (b) Transceivers and PC; (c) UAV used in experiments.

Figure 3 plots the cumulative distribution function (CDF) of the normalized channel amplitude based on 100 frames of data with and without UAV intrusion. From Figure 3, we can observe that the intrusion of the UAV causes an obvious variation in the CDF of the normalized channel amplitude. Thus, it is feasible to detect UAV intrusion by identifying such channel variations.

Figure 4 shows the CSI autocorrelation function and the threshold λ versus the frame number for a set of data collected under UAV intrusion. The UAV flies from a distance to the transceivers, and the shortest distance between the UAV and the receiver is about 8m. In Figure 4, although the CSI autocorrelation function shows some initial fluctuations, there is no instance of 3 (N_{Tol}) consecutive points that are either larger or less than the threshold during this time due to the adaptive adjustment of the threshold. In the 102-th frame, however, the CSI autocorrelation function decreases significantly. Consequently, a series of continuous values that are less than the threshold occurs, and thus, the algorithm identifies UAV intrusion at the 104-th frame.

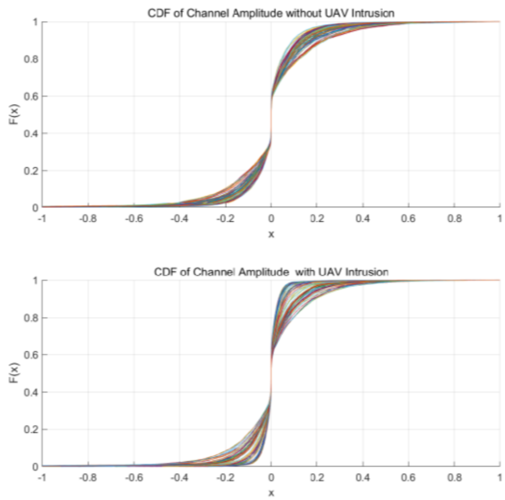

Figure 3. CDF of the normalized CSI without (Top) and with (Bottom) UAV Intrusion.

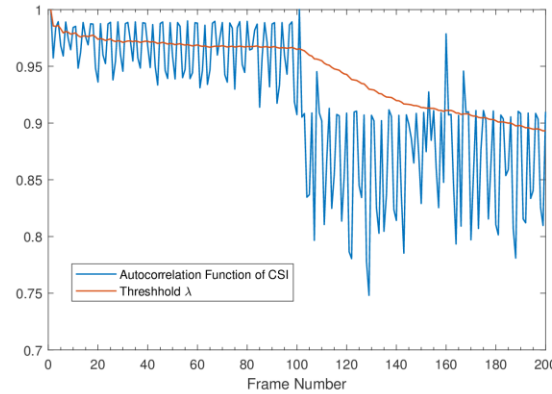

Figure 4. An Example of UAV Detection with the Proposed Method.

Figure 5 plots the autocorrelation function of the CSI versus the frame number with and without UAV intrusion at different distances between the UAV and the receiver. The CSI autocorrelation function with UAV intrusion is shifted lower with respect to that without UAV intrusion because the intrusion of the UAV leads to a decrease in the channel correlation over the interval d. The closer the UAV is to the receiver, the greater the impact on the channel. Therefore, the difference of the CSI autocorrelation function gradually decreases from the distance 1 meters, 3 meters to 10 meters. When the UAV is 10 meters away from the receiver, the difference of correlation function is already very small, which means 10 meters is close to the limit of detection distance.

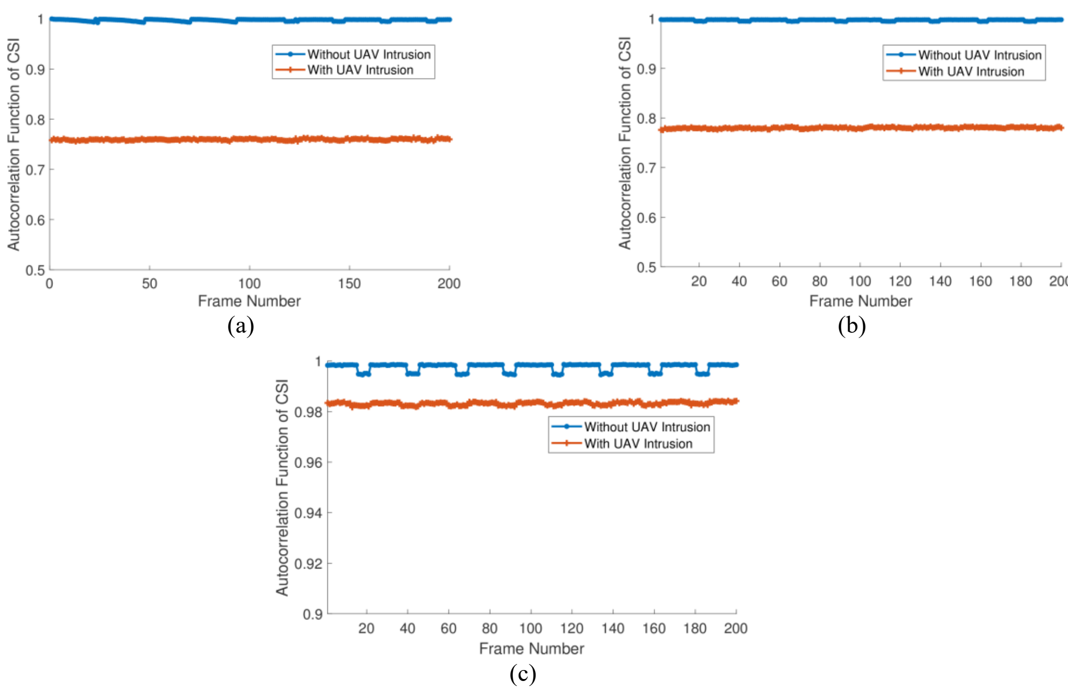

Figure 5. Comparison of the CSI Autocorrelation Function without and with UAV Intrusion when the distance between the UAV and the receiver is (a) 1m, (b) 3m, (c) 10m.

5. CONCLUSION

As the increasingly popular small UAVs brings security threats, more widely-deployed UAV detection is needed compared with traditional detection methods such as radar. This paper has proposed a UAV intrusion detection method based on CSI autocorrelation function for wireless communication link. The CSI with and without UAV intrusion was analysed and the proposed algorithm based on the CSI autocorrelation function was presented in detail. By successfully detecting the intrusion of UAV with the proposed method in the experiment, we verified the effectiveness of the proposed method. The experimental results show that the distance will affect the detection performance, but the presence or absence of UAV can still be judged within 10m.

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REFERENCES

[1] Kanellakis, C. and Nikolakopoulos, G., "Survey on computer vision for UAVs: Current developments and trends," Journal of Intelligent and Robotic Systems, 87, 141-168(2017).

[2] BBC News, "Drones ground flights at gatwick,", accessed 28 December 2021, https://www.bbc.com/news/uk-england-sussex-46623754, (2018).

[3] Zhao, Y. and Su, Y., "Cyclostationary phase analysis on micro-doppler parameters for radar-based small UAVs detection," IEEE. T. Instrum. Meas, 67(9), 2048-2057 (2018).

[4] Oh, B. S. and Lin, Z., "Extraction of global and local micro-doppler signature features from FMCW radar returns for UAV detection," IEEE. T. Aero. Elec. Sys, 57(2), 1351-1360(2021).

[5] Zhao, Y. and Su, Y., "The extraction of micro-doppler signal with EMD algorithm for radar-based small UAVs detection," IEEE. T. Instrum. Meas, 69(3), 929-940(2020).

[6] Xue, W., Qi, J., Shao, G., Xiao, Z., Zhang, Y. and Zhong, P., "Low-rank approximation and multiple sparse constraint modeling for infrared low-flying fixed-wing UAV detection," IEEE. J. Sel. Top. Appl, 14, 4150-4166(2021).

[7] Jamil, S., Fawad, Rahman, M. U., Ullah, A., Badnava, S., Forsat, M. and Mirjavadi, S. S., "Malicious UAV detection using integrated audio and visual features for public safety applications," Sensors, 20(14), 3923(2020).

[8] Zhang, S., Yang, G., Sun, T., Du, K. and Guo, J., "UAV detection with transfer learning from simulated data of laser active imaging," Applied Sciences, 11(11), 5182(2021).

[9] Dumitrescu, C., Minea, M., Costea, I. M., Cosmin Chiva, I. and Semenescu, A., "Development of an acoustic system for UAV detection," Sensors, 20(17), 4870(2020).

[10] Bisio, I., Garibotto, C., Lavagetto, F., Sciarrone, A. and Zappatore, S., "Unauthorized amateur UAV detection based on WiFi statistical fingerprint analysis," IEEE. Commun. Mag., 56(4), 106-111(2018).

[11] Alipour-Fanid, A., Dabaghchian, M., Wang, N., Wang, P., Zhao, L. and Zeng, K., "Machine learning-based delay-aware UAV detection and operation mode identification over encrypted Wi-Fi traffic,", IEEE. T. Inf. Foren. Sec, 15, 2346-2360(2020).

[12] Zhang, H., Cao, C., Xu, L. and Gulliver, T. A., "A UAV detection algorithm based on an artificial neural network," IEEE Access, 6, 24720-24728(2018).

[13] Nemer, I., Sheltami, T., Ahmad, I., Yasar, U. H. and Abdeen, M., "RF-based UAV detection and identification using hierarchical learning approach," Sensors, 21(6), 1947(2021).

[14] Ritchie, M., Fioranelli, F., Griffiths, H. and Torvik, B., "Micro-drone RCS analysis," Proc. 2015 IEEE Radar. Conf., 452-456(2015).