

DRONE SIGNAL DETECTION SYSTEM BASED ON MACHINE LEARNING

Field of invention

This invention relates to a method and a system that detects and identifies an
5 unmanned aerial vehicle (UAV). Particularly, this invention relates to a method and a
system that detects and identifies the presence of UAV based on uplink and/or
downlink signals.

Background

10 Traditionally, UAVs are used by government agencies for aerial monitoring
and/or surveillance purposes. However, as the technology of UAVs improves and
cost reduces, UAVs are now also widely used by the general public for aerial
photography, inspection of buildings, and patrols. As such uses by the general public
are unsupervised, problems are created due to such use. For example, it has
15 become common for UAVs to enter no-fly zones designated for aircraft in an airport
or high value premises designated for government office containing sensitive
information. Some UAVs have also been used in residential premises and such uses
invade the privacy of residents residing in the residential premises.

Existing UAV detection systems are based on classic radio frequency (RF)
20 signal processing method, which requires prior knowledge of UAV signals. This
requires constant market scan of latest UAV models and collating of these new UAV
signals. Hence, end users might not able to catch up with the latest UAVs available in
the market and such UAV detection systems would not be able to detect such UAVs.

Thus, those skilled in the art are constantly striving to provide a method and a
25 system that allows detection of UAVs without requiring prior knowledge of UAV
signals.

Summary of Invention

The above and other problems are solved and an advance in the state of the
30 art is provided by a method and/or a system in accordance with this disclosure. A
first advantage of a method and/or a system in accordance with embodiments of this

disclosure is that it allows detection of registered and unregistered UAVs without requiring prior knowledge of signals from UAVs. A second advantage of a method and/or system in accordance with embodiments of this disclosure is the implementation of machine learning that is able to train and detect UAVs based on communication protocols employed by the UAVs. In doing so, human resource is minimised. A third advantage of a method and/or system in accordance with embodiments of this disclosure is that it allows early intervention to prevent UAVs from entering restricted zones.

A first aspect of the disclosure relates to an Unmanned Aerial Vehicle (UAV) detection system. The UAV detection system comprises: an antenna, a radio receiver, a processor, a memory and instructions stored on the memory and executable by the processor to: receive IQ data from the radio, process the IQ data to form a spectrogram for the IQ data, and analyse the spectrogram image to determine if the signal received belongs to a UAV.

In an embodiment of the first aspect of the disclosure, the instruction to process the IQ data to form the spectrogram image comprises instructions to: apply a window function to the IQ data to filter out noise; transform the IQ data into frequency-domain data forming a spectrogram data; square the spectrogram data; apply averaging of the squared spectrogram data over several consecutive time blocks to form an initial spectrogram image; and convert the initial spectrogram image to a logarithmic scale.

In an embodiment of the first aspect of the disclosure, the window function is Blackman-Harris window.

In an embodiment of the first aspect of the disclosure, the instruction transform the IQ data into frequency-domain data comprises instructions to: apply a Fast Fourier Transform (FFT) to convert the IQ data from time-domain signal to frequency-domain signal; and stack the frequency-domain signals over several time blocks to form the spectrogram data.

In an embodiment of the first aspect of the disclosure, the spectrogram data is squared with the following expression: $|X[k]|^2 = |X_{re}[k]|^2 + |X_{im}[k]|^2$ where k

denotes the FFT subcarrier, X_{re} is the real (I) part of the frequency-domain signals and X_{im} is the imaginary (Q) part of the frequency-domain signals.

In an embodiment of the first aspect of the disclosure, the squared spectrogram data is averaged with the following expression:

$$Y[k] = \frac{1}{8} \sum_{i=0}^7 |X[k]|_i^2$$

5 where i is the time block.

In an embodiment of the first aspect of the disclosure, the initial spectrogram image is converted to a logarithmic scale with the following expression $R[k] = \log_{10}(Y[k] + 1)$.

10 In an embodiment of the first aspect of the disclosure, the logarithmic scale is within 0 to 255.

In an embodiment of the first aspect of the disclosure, the instruction to analyse the spectrogram image to determine if the signal received belongs to a UAV comprises instructions to: feed the spectrogram to a deep learning module to determine the presence of an uplink and/or downlink UAV signal.

15 A second aspect of the disclosure relates to a method of detecting an Unmanned Aerial Vehicle (UAV) comprising: receiving signals from a radio, the signals consisting of IQ data; processing the IQ data to form a spectrogram image; and analysing the spectrogram image to determine if the signal received belongs to a UAV.

20 In an embodiment of the second aspect of the disclosure, the step of processing the IQ data to form the spectrogram image comprises: applying a window function to the IQ data to filter out noise; transforming the IQ data into frequency-domain data forming a spectrogram data; squaring the spectrogram data; applying averaging of the squared spectrogram data over several consecutive time blocks to
25 form an initial spectrogram image; and converting the initial spectrogram image to a logarithmic scale.

In an embodiment of the first aspect of the disclosure, the window function is Blackman-Harris window.

In an embodiment of the first aspect of the disclosure, the step of transforming the IQ data into frequency-domain data comprises: applying a Fast Fourier Transform (FFT) to convert the IQ data from time-domain signal to frequency-domain signal; and stacking the frequency-domain signals over several time blocks to form the spectrogram data.

In an embodiment of the first aspect of the disclosure, the spectrogram data is squared with the following expression:

$$|X[k]|^2 = |X_{re}[k]|^2 + |X_{im}[k]|^2$$

where k denotes the FFT subcarrier, X_{re} is the real (I) part of the frequency-domain signals and X_{im} is the imaginary (Q) part of the frequency-domain signals.

In an embodiment of the first aspect of the disclosure, the squared spectrogram data is averaged with the following expression:

$$Y[k] = \frac{1}{8} \sum_{i=0}^7 |X[k]|_i^2$$

where i is the time block.

In an embodiment of the first aspect of the disclosure, the initial spectrogram image is converted to a logarithmic scale with the following expression $R[k] = \log_{10}(Y[k] + 1)$.

In an embodiment of the first aspect of the disclosure, the logarithmic scale is within 0 to 255.

In an embodiment of the first aspect of the disclosure, the step of analysing the spectrogram image to determine if the signal received belongs to a UAV comprises: feeding the spectrogram to a deep learning module to determine the presence of an uplink and/or downlink UAV signal.

Brief description of drawings

The above and other features and advantages of a method and a system in accordance with this invention are described in the following detailed description and are shown in the following drawings:

Figure 1 illustrating a block diagram of a system for detecting UAVs in accordance with this disclosure;

Figure 2 illustrating a block diagram of a processing system of the server for providing a system in accordance with an embodiment of this disclosure;

5 Figure 3 illustrating an application executable by the computing system in accordance with this disclosure;

Figure 4 illustrating a flow diagram of a process performed by the application in accordance with this disclosure;

10 Figure 5 illustrating the resultant image from step 435 of an uplink frequency hopping transmission of a DX7s controller used by UAVs in accordance with this disclosure;

Figure 6 illustrating the resultant image from step 435 of an uplink frequency hopping transmission of a DJ6 controller used by UAVs in accordance with this disclosure;

15 Figure 7 illustrating the resultant image from step 435 of a downlink video transmission of a typical UAV in accordance with this disclosure;

Figure 8 illustrating the resultant image from step 435 of background noise in accordance with this disclosure;

20 Figure 9 illustrating the resultant image from step 435 of an uplink transmission of a DX7s controller without Blackman-Harris windowing applied;

Figure 10 illustrating the resultant image from step 435 of an uplink transmission of a DX7s controller without averaging applied in step 425;

Figure 11 illustrating the resultant image from step 435 of an uplink transmission of a DX7s controller without converting into log scale in step 435; and

25 Figure 12 illustrating a Convolutional Neural Network (CNN) structure implemented by the deep learning module in accordance with this disclosure.

Detailed description

30 This invention relates to a method and a system that detects and identifies an unmanned aerial vehicle (UAV). Particularly, this invention relates to a method and a

system that detects and identifies the presence of UAV based on uplink and/or downlink signals.

It is envisioned that a system and/or method in accordance with embodiments of this disclosure may be used to detect UAVs based on spectrograms that are processed for each signal received from UAVs. Figure 1 illustrates system 100 for automatically detecting UAVs in accordance with this disclosure. Other than detecting UAVs, the system 100 also tracks the location and time of detection. The system 100 includes a computing system 110, an antenna 120 and a radio 130. Each UAV 190 will be controlled by a user via a remote controller 191. As the remote controller 191 is typically on the ground while the UAV is above ground, the communication from the remote controller 191 to the UAV 190 is known as uplink 196 while the communication from the UAV 190 to the remote controller 191 is known as downlink 195.

The radio 130 is a radio receiver capable of receiving radio frequency (RF) signals. The antenna 120, radio 130 and computing system 110 are installed at various strategic locations to monitor UAVs entering certain designation areas. The radio 130 receives surrounding RF signals, i.e. uplink and downlink, from the antenna 120 and converts the RF signals to IQ data. The antenna 120 and radio 130 are commercially available. Hence, the details of the antenna 120 and radio 130 are omitted for brevity.

Computing system 110 is a typical processing system such as a desktop computer, laptop computer, or other computer terminal that is connected to the radio 130 via either a wired or wireless connection to receive IQ data from the radio 130. Computing system 110 executes applications that perform the required processes in accordance with this disclosure. One skilled in the art will recognize that although only computing system 110 is shown, any number of processing systems may be connected and/or operating in parallel to perform the applications for providing embodiments of this disclosure without departing from this disclosure. Further details of the computing system 110 will be described below with reference to figure 2.

Processes are stored as instructions in a media that are executed by a processing system in computing system 110 or a virtual machine running on the

computing system 110 to provide the method and/or system in accordance with this disclosure. The instructions may be stored as firmware, hardware, or software. Figure 2 illustrates processing system 200 such as the processing system in computing system 110 that execute the instructions to perform the processes for providing a method and/or system in accordance with this invention. One skilled in the art will recognize that the exact configuration of each processing system may be different and the exact configuration of the processing system in each device may vary. Thus, processing system 200 shown in figure 2 is given by way of example only.

Processing system 200 includes Central Processing Unit (CPU) and/or Graphics Processing Unit (GPU) 205. CPU/GPU 205 is a processor, microprocessor, or any combination of processors and microprocessors that execute instructions to perform the processes in accordance with the present invention. CPU/GPU 205 connects to memory bus 210 and Input/ Output (I/O) bus 215. Memory bus 210 connects CPU/GPU 205 to memories 220 and 225 to transmit data and instructions between the memories and CPU/GPU 205. I/O bus 215 connects CPU 205 to peripheral devices to transmit data between CPU/GPU 205 and the peripheral devices. One skilled in the art will recognize that I/O bus 215 and memory bus 210 may be combined into one bus or subdivided into many other busses and the exact configuration is left to those skilled in the art.

A non-volatile memory 220, such as a Read Only Memory (ROM), is connected to memory bus 210. Non-volatile memory 220 stores instructions and data needed to operate various sub-systems of processing system 200 and to boot the system at start-up. One skilled in the art will recognize that any number of types of memory may be used to perform this function.

A volatile memory 225, such as Random Access Memory (RAM), is also connected to memory bus 210. Volatile memory 225 stores the instructions and data needed by CPU/GPU 205 to perform software instructions for processes such as the processes required for providing a system in accordance with this invention. One skilled in the art will recognize that any number of types of memory may be used as volatile memory and the exact type used is left as a design choice to those skilled in the art.

I/O device 230, keyboard 235, display 240, memory 245, network device 250 and any number of other peripheral devices connect to I/O bus 215 to exchange data with CPU/GPU 205 for use in applications being executed by CPU/GPU 205. I/O device 230 is any device that transmits and/or receives data from CPU/GPU 205.

5 Keyboard 235 is a specific type of I/O that receives user input and transmits the input to CPU/GPU 205. Display 240 receives display data from CPU/GPU 205 and display images on a screen for a user to see. Memory 245 is a device that transmits and receives data to and from CPU/GPU 205 for storing data to a media. Network device 250 connects CPU/GPU 205 to a network for transmission of data to and from other

10 processing systems.

In one embodiment, the system 100 comprises a computing system 110 that uses ARM CPU and Linux Operating System (OS) and is communicatively connected to the radio 130. In order to identify the location of a drone, multiple systems 100 may be implemented by installing the systems 100 at various locations strategically so that

15 a location of the UAV can be determined by way of triangulation. In another embodiment, the radio 130 may be equipped with a network device to allow transferring and receiving of information over a wired or wireless connection. The network device can receive and transmit data, execute software applications to pre-process the signals received to filter noise. This means that instead of providing

20 multiple ARM CPU and Linux OS at various locations, a low cost edge computing device can be provided for each system 100 where edge computing device of each system 100 is communicatively connected to the computing system 110 acting as a main server to perform more complex task such as that performed by the Deep Learning Module 330.

25 In order to further reduce the cost of having to furnish each network device with 3G/4G communication capability, the network device may be equipped with short and/or medium range wireless capability and wirelessly connects to a sub-server. The sub-server would subsequently transmit the signals to the computing system 110. Essentially, the sub-server reduces the cost of having to furnish each network

30 device with 3G/4G communication capability. If future network communication protocol includes Internet of Things (IoT) communication at a more cost efficient rate,

the network device may be configured to transmit the signals directly to the computing system 110.

Figure 3 illustrates a program 300 stored in memory or virtual memory of the computing system 110 for performing the processes in accordance with the disclosure. Program 300 includes a pre-processing module 320 and a deep learning module 330. Briefly, the processes executed by the 3 modules are as follows:

- 1) The pre-processing module 320 cleans up the spectrogram to ensure more effective Deep Learning inference in the next module.
- 2) The deep learning module 330 trains a dataset based on spectrogram received from the IQ module. It also performs Deep Learning inference on input spectrogram and produces an output on whether uplink and downlink drone signals are present or absent. The current GPU that is used by the prototype does not support training. Instead, training is executed by a server having higher capacity to support the training. Nevertheless, it is a possible that training can be executed by the computer system 110 with better GPU specifications.

The processes of each of the modules will now be described as follows.

Figure 4 illustrates a flow chart of a process 400 executed by the program 300 in accordance with an embodiment of this disclosure. Process 400 begins with step 405 by receiving a signal from the radio 130. The signals are captured by the radio 130. The signals are sampled at certain intervals. For example, the signals may be sampled at every 1 second and the sampled signals are stored in the memory. Assuming the signal is from a UAV, the signal comprises both uplink and downlink data. As mentioned above, the radio 130 receives surrounding RF signals, i.e. uplink and downlink, from the antenna 120 and converts the RF signals to IQ data. Hence, the signal received from the radio is already in IQ data format.

In step 410, process 400 applies a window function to filter out noise. Specifically, process 400 applies Blackman-Harris window to minimise side lobe levels. Blackman-Harris windowing enables the edges of frequency hopping or video transmission patterns in the spectrogram to be more sharp and distinct. This allows pattern recognition in Deep Learning Inference to be more effective. Specifically, the

coefficients of a Blackman-Harris window can be expressed with the following expression:

$$w[n] = a_0 - a_1 \cos\left(\frac{2\pi n}{N}\right) + a_2 \cos\left(\frac{4\pi n}{N}\right) - a_3 \cos\left(\frac{6\pi n}{N}\right)$$

$$a_0 = 0.35875; \quad a_1 = 0.48829; \quad a_2 = 0.14128; \quad a_3 = 0.01168.$$

Blackman-Harris window is well known in the art. Hence, the details of Blackman-Harris window are omitted for brevity.

In step 415, process 400 transforms the IQ data into frequency-domain data forming a spectrogram data. Specifically, process 400 applies a Fast Fourier Transform (FFT) to convert the IQ data from time-domain signal to a frequency-domain signal. Frequency domain signals are then stacked up over several time blocks to give a spectrogram data.

In step 420, process 400 squares the spectrogram data which is complex data output from FFT. The squaring of the spectrogram data can be expressed in the following expression:

$$|X[k]|^2 = |X_{re}[k]|^2 + |X_{im}[k]|^2$$

where k denotes the FFT subcarrier, X_{re} is the real (I) part of the frequency-domain signals and X_{im} is the imaginary (Q) part of the frequency-domain signals..

This ensures that the data fed into the Deep Learning module only consists of positive Real numbers.

In step 425, process 400 applies averaging of the spectrogram data over several consecutive time blocks to form an initial spectrogram image which can be expressed with the following expression:

$$Y[k] = \frac{1}{8} \sum_{i=0}^7 |X[k]|_i^2$$

where i is the time block.

Averaging over several time blocks improves Signal-to-Noise ratio of the signal as represented by the spectrogram when the random white noise are suppressed through averaging. This also allows the signal to be more visible for the Deep Learning model to perform inferencing. By averaging across the time domain,

more “hops” or patterns can be captured in a single 256x1024 spectrogram, allowing Deep Learning Inference to recognise and generalise the patterns more effectively.

In step 435, the spectrogram is converted to a logarithmic scale to form the processed spectrogram for the deep learning module 330. The spectrogram is converted to a logarithmic scale to ensure that they are within an effective range for CNN inference, which is from 0 to 255 as derived from pixel values of images which are the traditional inputs of CNN. The spectrogram is converted to a logarithmic scale with the following expression:

$$R[k] = \log_{10}(Y[k] + 1)$$

This allows the data values to be smaller which results in the Deep Learning Inference to be faster and more efficient.

Figure 5 illustrates an uplink frequency hopping of a DX7s controller's transmitter used by UAVs and figure 6 illustrates an uplink frequency hopping of another DX7s controller's transmitter used by UAVs. Figure 7 illustrated a downlink video transmission of a typical UAV. Figure 8 illustrates background noise, i.e. absence of UAV. Figures 5-8 are images produced after step 435.

In step 440, process 400 feeds the processed spectrogram to the deep learning module 330 to determine the presence of an uplink and/or downlink UAV signal.

Process 400 repeats from step 405 for the next IQ data after step 440.

Essentially, steps 405-435 in process 400 are executed by the pre-processing module 320 to reduce the amount of data so that the deep learning module 330 is able to determine the presence of UAV faster and more efficiently.

Figure 9 an uplink of a DX7s controller's transmitter without Harris Blackman applied. We can observe that the image of the spectrogram on figure 9 appears to be darker compared to the image of the spectrogram on figure 5. Figure 10 illustrates an uplink of a DX7s controller's transmitter without averaging applied in step 425. Figure 11 illustrates an uplink of a DX7s controller's transmitter without converting into log scale in step 435. We can observe that the image of the spectrogram on figure 11 appears to be darker compared to the image of the spectrogram on figure 5. On figures 9 and 10, while the image of the spectrogram on figures 9 and 10 may be

visually similar to the image of the spectrogram on figure 5, the data of the spectrogram on figures 9 and 10 are not the same as the data of the spectrogram on figure 5.

Figure 12 illustrates a CNN structure 1200 implemented by the deep learning module 330 in accordance with this disclosure. The CNN structure 1200 comprises a Convolutional Layer having six convolutional blocks 1205-1230, a Global MaxPooling Layer 1235 and 2 Dense Layers 1240 and 1245. The input 1201, which is the processed spectrogram, is a spectrogram of size 256x1024, where 256 represent the time domain blocks and 1024 represent the frequency domain bins. In short, the input 1201 has a shape of 1x256x1024.

The input 1201 is fed to the Convolutional Layer in the following sequence, First Convolutional Block 1205 → Second Convolutional Block 1210 → Third Convolutional Block 1215 → Fourth Convolutional Block 1220 → Fifth Convolutional Block 1225 → Sixth Convolutional Block 1230. The details of each block are as follows.

- First Convolutional Block 1205: Convolutional Layer of 16 filters with kernel size of 15x15, followed by a RELU layer and a Maxpooling layer of shape 2x2
- Second Convolutional Block 1210: Convolutional Layer of 32 filters with kernel size of 3x3, followed by a RELU layer and a Maxpooling layer of shape 2x2
- Third Convolutional Block 1215: Convolutional Layer of 64 filters with kernel size of 3x3, followed by a RELU layer and a Maxpooling layer of shape 2x2
- Fourth Convolutional Block 1220: Convolutional of 128 filters with kernel size of 3x3, followed by a RELU layer and a Maxpooling layer of shape 2x2
- Fifth Convolutional Block 1225: Convolutional Layer of 256 filters with kernel size of 3x3, followed by a RELU layer and a Maxpooling layer of shape 2x2
- Sixth Convolutional Block 1230: Convolutional Layer of 512 filters with kernel size of 3x3, followed by a RELU layer and a Maxpooling layer of shape 2x2

After the sixth convolutional block 1235, the data's dimensionality is further reduced by applying a Global MaxPooling Layer 1235. Apart from reducing the data's dimension, global max pooling provides for translational invariance, reduces over-

fitting and increases the generalization abilities for this machine learning model when applied to drone signals.

After the Global MaxPooling Layer 1235, the data is fed into two dense layers, First Dense Layer 1240 and Second Dense Layer 1245. The First Dense Layer 1240
5 has an output dimension of 128 and the Second Dense Layer 1245 has an output dimension of 2. Hence, the output of the CNN structure 1200 contains 2 classes namely, “presence of drone” and “absence of drone”. The same CNN is used for both uplink and downlink detections independently.

The above is a description of embodiments of a system in accordance with
10 the disclosure as set forth below. It is envisioned that those skilled in the art can and will design alternative embodiments of this disclosure based upon this disclosure that infringe on this disclosure as set forth in the following claims.

Claims

1. An Unmanned Aerial Vehicle (UAV) detection system comprising:
a radio, a processor, a memory and instructions stored on the memory and
5 executable by the processor to:
receive IQ data from the radio;
process the IQ data to form a spectrogram image; and
analyse the spectrogram image to determine if the signal received belongs to
a UAV.
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2. The UAV detection system according to claim 1 wherein the instruction to
process the IQ data to form the spectrogram image comprises instructions to:
apply a window function to the IQ data to filter out noise;
transform the IQ data into frequency-domain data forming a spectrogram
15 data;
square the spectrogram data;
apply averaging of the squared spectrogram data over several consecutive
time blocks to form an initial spectrogram image; and
convert the initial spectrogram image to a logarithmic scale.
20
3. The UAV detection system according to claim 2 wherein the window function
is Blackman-Harris window.
4. The UAV detection system according to claim 2 wherein the instruction to
25 transform the IQ data into frequency-domain data comprises instructions to:
apply a Fast Fourier Transform (FFT) to convert the IQ data from time-domain
signal to frequency-domain signal; and
stack the frequency-domain signals over several time blocks to form the
spectrogram data.
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5. The UAV detection system according to claim 4 wherein the spectrogram data is squared with the following expression:

$$|X[k]|^2 = |X_{re}[k]|^2 + |X_{im}[k]|^2$$

where k denotes the FFT subcarrier, X_{re} is the real (I) part of the frequency-domain signals and X_{im} is the imaginary (Q) part of the frequency-domain signals.

6. The UAV detection system according to claim 5 wherein the squared spectrogram data is averaged with the following expression:

$$Y[k] = \frac{1}{8} \sum_{i=0}^7 |X[k]|_i^2$$

where i is the time block.

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7. The UAV detection system according to claim 6 wherein the initial spectrogram image is converted to a logarithmic scale with the following expression $R[k] = \log_{10}(Y[k] + 1)$.

15 8. The UAV detection system according to claim 7 wherein the logarithmic scale is within 0 to 255.

9. The UAV detection system according to claim 1 wherein the instruction to analyse the spectrogram image to determine if the signal received belongs to a UAV comprises instructions to:

20 feed the spectrogram to a deep learning module to determine the presence of an uplink and/or downlink UAV signal.

10. A method of detecting an Unmanned Aerial Vehicle (UAV) comprising:
25 receiving IQ data from a radio;
processing the IQ data to form a spectrogram image; and
analysing the spectrogram image to determine if the signal received belongs to a UAV.

11. The method according to claim 1 wherein the step of processing the IQ data to form the spectrogram image comprises:

applying a window function to the IQ data to filter out noise;

5 transforming the IQ data into frequency-domain data forming a spectrogram data;

squaring the spectrogram data;

applying averaging of the squared spectrogram data over several consecutive time blocks to form an initial spectrogram image; and

10 converting the initial spectrogram image to a logarithmic scale.

12. The method according to claim 11 wherein the window function is Blackman-Harris window.

13. The method according to claim 11 wherein the step of transforming the IQ data into frequency-domain data comprises:

applying a Fast Fourier Transform (FFT) to convert the IQ data from time-domain signal to frequency-domain signal; and

stacking the frequency-domain signals over several time blocks to form the

20 spectrogram data.

14. The method according to claim 13 wherein the spectrogram data is squared with the following expression:

$$|X[k]|^2 = |X_{re}[k]|^2 + |X_{im}[k]|^2$$

25 where k denotes the FFT subcarrier, X_{re} is the real (I) part of the frequency-domain signals and X_{im} is the imaginary (Q) part of the frequency-domain signals.

15. The method according to claim 14 wherein the squared spectrogram data is averaged with the following expression:

$$Y[k] = \frac{1}{8} \sum_{i=0}^7 |X[k]|_i^2$$

where i is the time block.

16. The method according to claim 15 wherein the initial spectrogram image is converted to a logarithmic scale with the following expression $R[k] = \log_{10}(Y[k] + 1)$.

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17. The method according to claim 16 wherein the logarithmic scale is within 0 to 255.

18. The method according to claim 10 wherein the step of analysing the spectrogram image to determine if the signal received belongs to a UAV comprises:

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feeding the spectrogram to a deep learning module to determine the presence of an uplink and/or downlink UAV signal.

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