

High-Speed Telescope Autofocus for UAV Detection and Tracking

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Abstract: This paper presents the analysis, implementation and experimental evaluation of a high-speed automatic focus module for a telescope-based UAV detection and tracking system. An existing optical drone detection system consisting of two telescopes and deep learning-based object detection is supplemented by suitable linear stages and passive focus algorithms to enable fast automatic focus adjustment. Field tests with the proposed system demonstrate that UAVs flying at speeds of up to 24 m/s towards the system are successfully tracked and kept in focus from more than 4500 m down to 150 m. Furthermore, different search functions and contrast measures are evaluated and it is shown that the Tenengrad operator combined with the Hill Climbing search function achieve the best performance for focusing on fast moving small UAVs.

1. Introduction

In recent years the necessity of optical detection systems, which are capable of detecting and tracking small, fast and agile unmanned aerial vehicles (UAVs) has become evident as numerous incidents illustrate the growing threat to public safety and infrastructure. A famous example is the shutdown of the London Gatwick airport for more than a day in 2018 due to a nearby UAV and in 2023 the airport had to cease operation for an hour again due to a suspected UAV [1]. In 2022 UAVs were sighted close to nuclear power plants and government buildings in Sweden [2]. Other incidents involve the smuggling over state borders and prisons [3, 4] or the disruption of sporting events [5]. Early detection of illegally intruding UAVs to safety critical areas is paramount to prepare an appropriate response to a possibly hazardous situation.

UAV detection is generally performed in a multispectral manner, combining various sensor technologies, like RADAR [6], radio frequency [7], acoustics [8] and electro-optics [9], into a holistic system [10, 11]. An essential component of such a system is the electro-optical sensor, as it allows the most conclusive situational assessment through visual images. These optical sensors have a narrow field of view (FoV) and use mounts for pan and tilt movement [12]. Detection of UAVs is facilitated via computer vision algorithms, with convolutional neural networks, like YOLO [13], FRCNN [14] or Retinanet [15] outperforming conventional methods [16]. To achieve long detection ranges for small UAVs, the latest research incorporates telescopes, which allow larger apertures and thus, better resolution, to extend the operational range to more than 4 km [9]. The usage of optics with long focal lengths and large apertures result in a narrow depth of field (DoF), which increases the demand on a fast automatic focus especially when tracking high-speed UAVs.

The automatic focus is characterized into two categories: active and passive focusing methods. Active focus methods measure the distance to the object through time of flight or ultrasonic sensors to adjust the focus accordingly [17, 18]. The most common passive focus technique is phase detection, which divides the incoming light rays into pairs of beams and by comparing them, the focus direction and distance to the best focus position is determined [19]. Although this method is fast and does not require much computational power, additional sensors and optical elements as well as a precise alignment are necessary.

46 Passive contrast-based methods find the optimal focus position by comparing the contrast
47 values of multiple images after shifting the camera sensor with respect to the optics in axial
48 direction [20] or in the case of telescope systems, the mirrors with respect to each other [21].
49 Contrast functions can be divided into five major groups: Gradient-, Laplace-, Wavelet-, Statistics-
50 and Discrete Cosine Transform based methods [22]. A well-known example of the gradient-
51 based group is the Tenengrad operator [23], which has shown promising results, when applied
52 using telescope systems and focusing on terrestrial objects like buildings [24]. Likewise, the
53 Normalized Variance [25], also a gradient-based approach, achieves good results for astronomical
54 observations [26]. To focus on very small image regions, as necessary for detection and tracking
55 of small UAVs, the Variance of Laplacian [27] and the Discrete Wavelet Transform operator
56 have proven to be good choices [28]. A variety of algorithms exist, which try to maximize the
57 contrast value and thus the sharpness of the image, like the Hill Climb [29], Fibonacci or Binary
58 algorithm [20, 30], curve fitting [31] or Gaussian fitting [32] etc.

59 Passive autofocus with contrast detection is frequently used in telescope-based imaging systems.
60 However, the main applications are concentrated around focusing on large scale objects like
61 buildings or for astronomical observations, which do not require a fast focus, but rather high
62 precision [24, 26]. Passive high-speed autofocus methods for long focal lengths have been
63 implemented for Time Delay Integration (TDI) cameras, which take continuous measurements at
64 250 Hz and estimate the maximum focus position through polynomials [33]. For the use case
65 of telescope-based UAV detection and tracking, challenges arise through the movement of the
66 UAV itself during the focusing phase, which introduces noise to the passive focus measurement.
67 Furthermore, high UAV velocities require fast focusing speed to keep the UAV in focus.

68 The contribution of this paper is the analysis, implementation and evaluation of a fast passive
69 autofocus module for a telescope-based UAV detection and tracking system. A high-speed
70 linear stage is used to reposition the camera with respect to the telescope in accordance to the
71 focus algorithm output. The article is organized as follows. Section 2 shows the analysis of the
72 requirements for the autofocus module. In Section 3 the implemented hardware and software
73 system is described in detail. The experiments and results are shown in Section 4 followed by a
74 conclusion in Section 5.

75 2. System analysis

76 To derive the hardware specifications for the automatic focus, the requirements for a telescope-
77 based UAV detection and tracking system are necessary. The operational range of the system is
78 given from 150 m to 5000 m and it shall be possible to track for example a DJI Mavic 3, which
79 has a diameter of 0.3 m and a maximum speed of 21 m/s. For reliable long distance detection of
80 UAVs, at least 15 x 15 pixels covering the object are required [9]. Therefore, the focal length of
81 the optical system should range from approximately 400 mm for closer distances to 2500 mm to
82 resolve objects at long distances.

83 2.1. Travel range

84 To enable focusing over the entire operational range, either the camera has to be moved with
85 respect to the telescope or the telescope mirrors have to be repositioned with respect to each
86 other. For the analysis it is assumed, that the camera is moved. To calculate the required travel
87 range necessary for the focus, the thin lens model [34] is used, where the image distance I is
88 determined by

$$I = \frac{1}{\frac{1}{f} - \frac{1}{x}}, \quad (1)$$

89 with f being the focal length of the telescope and x is the distance to the object. The necessary

90 focus range range is calculated to 1 mm for a focal length of 400 mm and 41.3 mm for a focal
91 length of 2500 mm.

92 2.2. Focus velocity

93 To keep fast UAVs in focus, a high focus velocity is crucial. Using Eq. 1 and assuming a
94 challenging case, of a DJI Mavic 3 flying at 21 m/s towards the telescope system in the closest
95 specified distance of 150 m, the required minimum focus velocity is 0.15 mm/s using a $f = 0.4$ m
96 telescope and 6 mm/s using a $f = 2.5$ m telescope.

97 2.3. Focus accuracy

98 The required focus accuracy is deduced from the DoF, given by

$$DoF = \frac{2xDfc(x-f)}{D^2f^2 - c^2(x-f)^2}, \quad (2)$$

99 where D is the aperture, f is the focal length, c is the circle of confusion and x is the distance
100 to the object [35]. Following guidelines of photography c is determined by $d/1500$, with d being
101 the camera sensor diagonal [36]. Fig. 1 shows the DoF of two focal lengths and an aperture of
102 0.3 m, assuming an 1 inch camera sensor with a diagonal of 15.86 mm the resulting c is 0.01 mm.
103 The minimal required focus accuracy is calculated by using the DoF of the closest distance of the
104 object of 150 m. For a focal length of 0.4 m the DoF is 4 m, which translates to a necessary focus
105 accuracy of 28 μm . Within these 4 m, the optical system captures a sharp image for a human
106 observer [36]. For the longer focal length of 2500 mm the minimum accuracy is 285 μm .

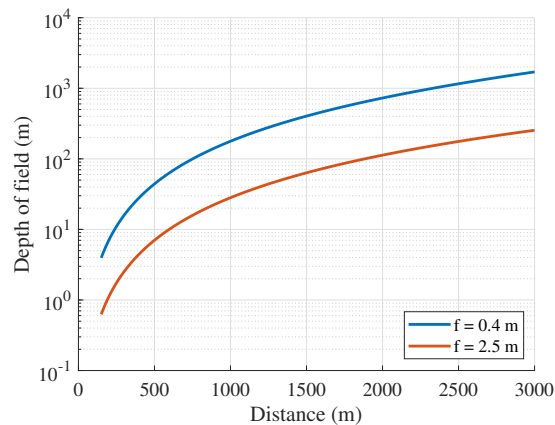


Fig. 1. DoF over distance to the observed object for the given focal lengths of the optical system assuming an 1 inch camera sensor.

107 3. System implementation

108 The implemented system is depicted in Fig. 2 and consists of two telescopes, an $f/10$ Meade
109 Schmidt Cassegrain telescope (LX200-ACF, Meade Acquisition Corp., Watsonville, USA) with
110 a focal length of 2.54 m and an ASA UWF300 telescope (ASA Astrosysteme GmbH, Neumarkt,
111 Austria) with a focal length of 0.39 m and an aperture of 0.3 m. The telescopes are attached
112 to a DDM100 mount (ASA Astrosysteme GmbH) to enable pan and tilt motion. To capture

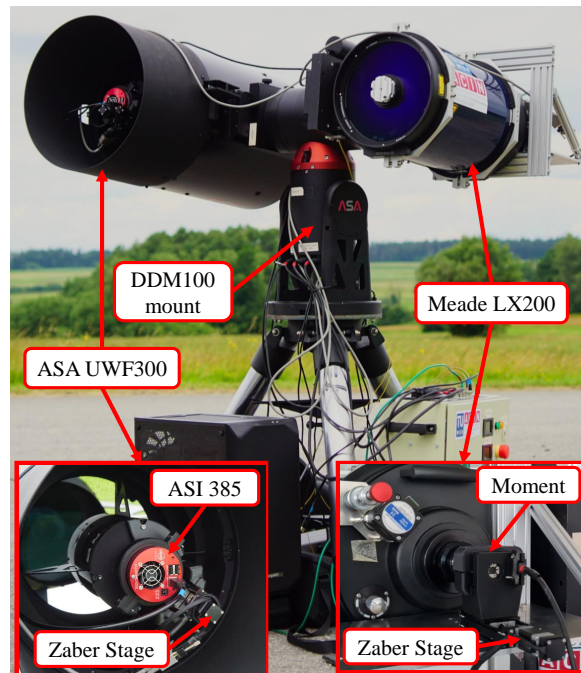


Fig. 2. The implemented dual telescope-system with the custom autofocus module consisting of a linear stage and an ASI camera for the ASA UWF 300 telescope and an additional stage for the Meade telescope, which adjusts the focus for the Moment camera.

113 images, the Meade telescope is equipped with a Moment scientific CMOS camera (Teledyne
114 Photometrics, USA), with a sensor diagonal of 17.5 mm and an ASI 385 MC-Cool camera (ZWO
115 Company, Suzhou, China) with a sensor diagonal of 8.4 mm is attached to the UWF300 telescope.
116 Following the analysis presented in Section 2, two linear stages of the type LSM050B-E03T4
117 (Zaber Technologies Inc., Vancouver, Canada) together with corresponding controllers X-MCB1
118 are used to reposition the cameras with respect to the telescopes. The stage offers a travel range
119 of 50.8 mm with a travel speed of 104 mm/s, while maintaining an accuracy of 3.5 μm . Both
120 cameras are mounted to the stages using custom-made adapters. Implementing the passive focus
121 by repositioning the cameras, rather than the telescope mirrors, is selected, as the latter approach
122 is too slow for the intended application.

123 3.1. Software architecture

124 The system architecture is depicted in Fig. 3, whereas the software components, the camera, the
125 object detector and the autofocus component are running in parallel [37]. The camera captures
126 images, that are provided to the deep learning object detector, as developed and trained to detect
127 UAVs in [37], and the autofocus component. For object detection, a fine-tuned FRCNN object
128 detector is used, which is trained on a custom UAV dataset [37]. The autofocus component issues
129 position commands to the stage driver, which controls the linear stage to position the camera
130 with respect to the telescope.

131 The automatic focus consists of two phases. First, the operational range is scanned in z direction

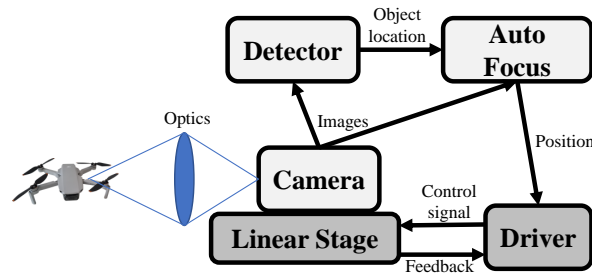


Fig. 3. Overview of the system architecture. The camera provides images to the object detector and autofocus algorithm, which send commands to the stage driver. The stage driver controls the linear stage, that physically moves the camera with respect to the optics to set the focus.

132 in the search for a UAV. Once a UAV is detected by the object detection algorithm and a bounding
 133 box shows the location of the UAV within an image, the focus optimization phase starts. During
 134 the optimization phase, the search algorithm tries to maximize the contrast value within the
 135 bounding box, by moving the camera with respect to the telescope and comparing the contrast
 136 of multiple images. For the calculation of the contrast, three functions are implemented and
 137 evaluated, namely the Tenengrad operator [23]

$$FV_{Tenengrad} = \sum_n^N \sum_m^M \nabla_x I(n,m)^2 + \nabla_y I(n,m)^2, \quad (3)$$

138 the Variance of Laplacian [27]

$$FV_{VarLap} = \frac{\sum_n^N \sum_m^M (\Delta I(n,m) - \overline{\Delta I})^2}{\overline{\Delta I}}, \quad (4)$$

139 and the Normalized Variance [25]

$$FV_{NVar} = \frac{\frac{1}{NM} \sum_n^N \sum_m^M (I(n,m) - \overline{I(n,m)})^2}{\overline{I}}, \quad (5)$$

140 where $I(n,m)$ is the image intensity of the pixel at the position n and m , N and M the overall
 141 size of the cropped image and \overline{I} the average image intensity. Three search algorithms, which
 142 are responsible to maximize the contrast value, are selected and evaluated. The Hill Climb
 143 Algorithm [29] moves the camera stepwise into one direction, until the contrast value starts to
 144 decrease and then moves it in the other direction with a smaller step size. The Binary and the
 145 Fibonacci Algorithm [30] divide the search space in a binary and Fibonacci pattern respectively.
 146 The focus optimization is triggered periodically after 3 s to keep the UAV in focus, to ensure a
 147 continuous track.

148 4. Experiments and results

149 To evaluate the system, various field tests are performed with UAVs to analyse the contrast
 150 functions, the search algorithms and the required speed of the autofocus.

Table 1. Results of the evaluation of the contrast functions for both the UWF and the Meade telescope after each contrast function is normalized to 1. Furthermore the data shows the mean of 8 measurements per telescope. The best results are marked in bold.

Name	Sensitivity	Local maxima	Position error
Normalized Variance (UWF)	1.56	9.43	0.113 mm
Tenengrad (UWF)	2.95	2.43	0.015 mm
Variance of Laplacian (UWF)	1.34	1.86	0.027 mm
Normalized Variance (Meade)	1.96	8.12	0.55 mm
Tenengrad (Meade)	5.16	2.75	0.23 mm
Variance of Laplacian (Meade)	1.38	6.12	0.35 mm

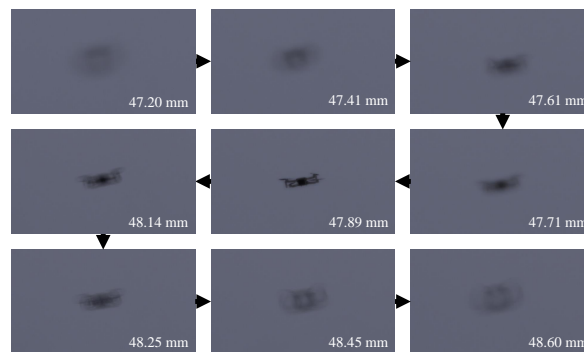


Fig. 4. A sequence of nine selected images from a linear stage scan to obtain the contrast measurement is depicted for the evaluation shown in Table 1. The white numbers within the images indicate the current stage position.

151 4.1. Contrast functions

152 To evaluate the contrast functions, a scan with the linear stage is performed, while filming for
 153 example a drone as seen in Fig. 4. Then, the contrast functions from Eq. 3 to Eq. 5 are applied to
 154 the images to obtain the contrast value per stage position and contrast function. The results of
 155 each function are normalized to 1 respectively as seen in Fig. 5.

156 The metrics used for the analysis are the sensitivity, the mean number of local maxima and the
 157 position error [26]. It is desirable to minimize the number of local maxima across the curve, as
 158 this reduces the probability of the search algorithm to stop focusing at a wrong position. Ideally,
 159 only one global maximum is present, which is the object to be tracked. The sensitivity of the
 160 curve is defined as the ratio between the maximum value divided by the mean of the contrast
 161 values, which are smaller than the mean of the contrast curve itself. A high sensitivity, therefore,
 162 manifests itself as a prominent peak. Finally, the position error shows the offset between the
 163 stage position of the maximum value of the measured contrast curve with respect to the manually
 164 selected best focus position.

165 Table 1 shows the mean value of 8 linear stage scan measurements performed with each telescope
 166 respectively. For both telescopes, the Normalized Variance has the worst performance in terms

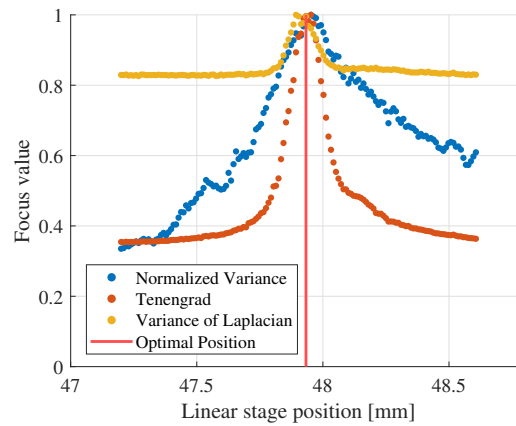


Fig. 5. Contrast values calculated using three different contrast measures for a linear stage scan, which contains a single UAV in the image in front of a clear sky.

Table 2. Results of approximately 450 tests of the search algorithms per telescope for the UWF and the Meade telescope. The values represent the mean, whereas the standard deviation is shown in brackets. The best results are marked in bold.

Name	Steps	Total distance (mm)	Time (s)	Accuracy (mm)
Hill (UWF)	9.2 (3.1)	1.1 (0.6)	1.4 (0.5)	-0.004 (0.1)
Binary (UWF)	25.3 (7.5)	3.8 (2.4)	3.4 (1.1)	-0.07 (0.3)
Fibonacci (UWF)	15.6 (3.3)	2.9 (1.4)	2.2 (0.8)	-0.002 (0.2)
Hill (Meade)	7 (1.6)	30 (13)	2.4 (0.7)	-0.46 (1.4)
Binary (Meade)	41.5 (11.5)	67.2 (40)	7.8 (2.5)	-0.58 (1.6)
Fibonacci (Meade)	23.3 (6.3)	44.5 (28.9)	4.8 (1.8)	-0.62 (3.1)

167 of all three evaluation metrics. The Tenengrad and Variance of Laplacian achieve similar results
 168 in terms of position error, however, Tenengrad shows a higher sensitivity and a lower number of
 169 maxima and is, therefore, found to be the best performing contrast function for the task of focusing
 170 on small objects like UAVs. Furthermore, the position error is below the required accuracy as
 171 determined using Eq. 2 in Section 2.

172 4.2. Search algorithms

173 Another crucial aspect for a reliable contrast-based automatic focus is a deterministic optimization
 174 function to maximize the contrast value and thus find the best focus position. Fast moving UAVs
 175 paired with the large apertures and low DoF of the optical detection system, require a quick
 176 termination of the optimization algorithm.

177 As evaluation metrics the number of linear stage steps, the total distance travelled, the elapsed
 178 time from the start to end of the optimization and the accuracy, defined as the offset to the
 179 manually set best focus position, are selected. For the experiments, the UAV is maintaining a

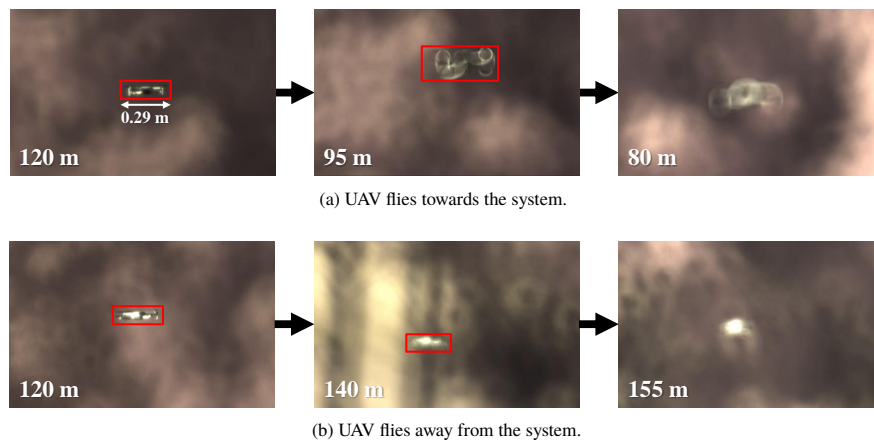


Fig. 6. Image sequence showing the DL-DoF test for the object detection algorithm. The initial focus is set manually, which is depicted on the left two images showing a distance to the UAV of 120 m. Then, the UAV flies towards 6a or away 6b from the system, while the focus is not adjusted. To obtain the DL-DoF, the distance is recorded, when the object detector fails, as seen in the right most images.

180 stationary position and the manually set optimal focus position is noted. Then, the image is
181 defocused by offsetting the linear stage from the optimal focus position by up to 0.5 mm for the
182 UWF and 5 mm for the Meade telescope. In the next step, the object detector is started, which
183 triggers the search algorithm and thus the contrast maximization for the detected bounding box.
184 During the evaluation of the search algorithms, the Tenengrad operator is used to obtain the
185 contrast value.
186 Table 2 shows the results of the optimization functions for both telescopes, whereas each value
187 represents the mean of approximately 450 tests and the standard deviation is shown in brackets.
188 For both telescopes, the Hill Climbing optimization algorithm scores the best or close to best
189 results according to all four metrics.

190 4.3. Speed and DoF

191 Finally, the speed and apparent deep learning DoF (DL-DoF) of the system is experimentally
192 evaluated. The DoF calculated for the UWF telescope in a distance of 150 m is 4 m, which
193 represents the depth of a completely sharp image. However, UAVs in slightly defocused images
194 can still be detected using deep learning algorithms [9]. To experimentally evaluate the DL-DoF
195 of the deep learning algorithm, a UAV is maintaining a certain distance to the system and the
196 focus is set manually to obtain a sharp image. Then, without adjusting the focus, the UAV flies
197 towards or away from the system, slowly going out of focus until the deep learning algorithm fails
198 to detect the UAV as seen in Fig. 6. Using this method the DL-DoF of the UWF telescope for the
199 most challenging case in a close distance of 120 m is determined to be approximately 75 m. The
200 distances are obtained by extracting the GPS position from the UAV remote controller. Within
201 this DL-DoF the UAV is quite defocused, however, still detectable by the deep learning algorithm.
202 Therefore, the requirements towards the stage accuracy can be relaxed. As the measured DL-DoF
203 represents the maximum DoF before the detector fails, for the calculation of the more tolerant
204 accuracy a DL-DoF of 15 m is assumed to ensure robust detection of objects. Referring back to
205 Eq. 2, the new more tolerant circle of confusion for object detection is calculated to be 0.06 mm

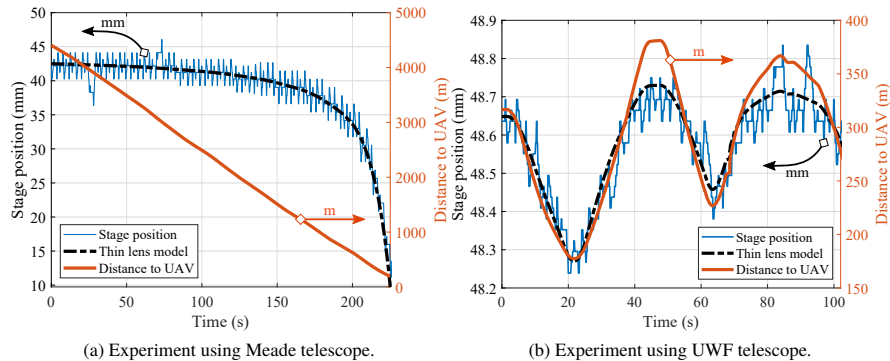


Fig. 7. Example data of successful continuous tracking and automatic focusing onto UAVs flying at speeds of up to 24 m/s towards the telescope system. The black dashed line shows the thin lens model, which fits well into the actual stage position. In Fig. 7a the non linear dependency between the UAV distance towards the linear stage position is visible, as defined by Eq. 1. The apparent noise of the stage position around the thin lens model is the optimization by the hill climb algorithm, which is periodically triggered to keep the UAV in focus as it moves.

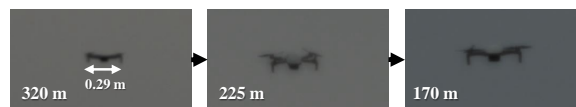


Fig. 8. Example image sequence depicting a UAV flying at up to 15 m/s towards the telescope system, while the automatic focus keeps the UAV in focus.

206 resulting in a necessary positioning accuracy of 0.16 mm for the UWF and 1.3 mm for the Meade
 207 telescope. These more tolerant constraints approve the relatively large standard deviations of the
 208 accuracy measured in Table 2.
 209 To evaluate the speed required by the focus module to keep up with the autofocus, experiments
 210 are performed with quad-copter and fixed wing UAVs. The DJI Mini 2 with a maximum speed
 211 of 16 m/s and a width of 289 mm and DJI Mavic 3 are used as quad-copter. The utilized fixed
 212 wing drone achieves a maximum speed of 41 m/s with a wingspan of 5 m. Fig. 7 shows two
 213 example flight trajectories together with some example images in Fig. 8, where a UAV is tracked
 214 continuously and the automatic focus is ensuring that the UAV stays in focus. During the tests
 215 the Tenengrad operator together with the Hill climbing search algorithm are used, whereas the
 216 autofocus optimization is triggered every 3 s. The maximum speed of the UAV flying towards the
 217 telescope system is recorded at 24 m/s resulting in a maximum stage velocity of 12 mm/s for the
 218 Meade telescope as shown in Fig. 7a. The necessary speed of the linear stage is higher than the
 219 calculated speed in Section 2, as the contrast based method requires multiple measurements at
 220 different stage positions to find the best focus. Also the UAV speeds during the tests are slightly
 221 higher than the assumed values in the system analysis. Fig. 7a confirms the calculated required
 222 travel range for the linear stage using the Meade telescope in Section 2.
 223 In summary, by periodically running the automatic focus, continuous detection and tracking
 224 of UAVs flying a speeds of up to 24 m/s from more than 4500 m down to 150 m towards the

225 telescope system is possible, as the focus module ensures a sharp image.

226 5. Conclusion

227 An automatic focus module for a telescope system is presented, which enables it to keep small
228 and fast moving UAVs in focus. Following the analysis and an integration of a suitable linear
229 stage, it is experimentally validated that the Tenengrad contrast measure and the Hill Climb
230 search algorithms show the best performance for the task of focusing fast and precisely onto
231 small UAVs within a telescope image. Furthermore, it is demonstrated, that the designed focus
232 module keeps a UAV, flying at a speed of 24 m/s, at a worst case distance of 150 m in focus when
233 using the $f/10$ Meade telescope with a focal length of 2540 mm, resulting in a stage velocity of
234 up to 12 mm/s. This enables detection and continuous tracking of UAVs flying at high speeds
235 towards the telescope system as the focus module ensures that the UAV remains in focus. Future
236 work will be centred around an efficient search pattern, which includes the pan and tilt motion of
237 the mount and the focus of the camera, to reduce the time needed until the object detector finds a
238 UAV and the optimization phase is triggered. Furthermore, the effects of the bounding box size
239 onto the focusing performance, especially in front of complex backgrounds will be investigated.

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246 8. Disclosures

247 The authors declare that there are no conflicts of interest related to this paper.

248 9. Data availability

249 Data underlying the results presented in this paper are not publicly available at this time but may
250 be obtained from the authors upon reasonable request.

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