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Radiometric Quality Assessment of Video Sequences Acquired from UAV Photogrammetric Systems

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Abstract. The issue of imagery data collection and its implementation in photogrammetric studies with the use of unmanned aerial vehicles is still valid and provides a wide field of research in the creation of new and expansion of existing solutions. It is particularly important to increase the accuracy of photogrammetric products. These days low altitude unmanned aerial vehicles are being used more and more often in photogrammetric applications. Compact digital cameras had acquired single, high-resolution imagery. Data obtained from low altitudes were often (and still are) used in mapping and 3D modelling. Due to the low costs of flights of UAV systems in comparison with traditional flights, applications of such platforms are also attractive for many remote sensing applications. However, due to the use of non-metric video cameras, one of the main problems when trying to automate the video data processing, is the video sequences' relatively poor radiometric quality. The article addresses the issue of assessing the quality of the video imagery acquired from a low altitude UAV platform. The Authors presented quality Indicators dedicated to UAV video sequences. The method is based on the analysis of the video stream, obtained in the different weather and lighting conditions. As a result of the research, an objective quality index for video acquired from low altitudes was determined.

Keywords: low altitude photogrammetry, unmanned aerial vehicle, video, radiometric quality.

Conference topic: Technologies of geodesy and cadastre.

Introduction

Unmanned Aerial Vehicles equipped with imaging sensors are an interesting and current research topic in photogrammetry. Up to now, research related to the processing of data obtained from low altitudes were mainly related to the images recorded with compact digital cameras (Sužiedelytė-Visockienė *et al.* 2016a; Kedzierski *et al.* 2016). Due to the flight height images were characterized by very high spatial and radiometric resolution.

Currently, the main topic in modern low altitude photogrammetry is analyzing the possibility of developing processing algorithms for UAV video sequences (Hannes, Nebiker 2007). Acquisition of imagery data from the unmanned aerial vehicles has now become a viable alternative to classical photogrammetry (Sužiedelytė-Visockienė *et al.* 2016b; Przyborski *et al.* 2015), especially in terms of mapping small areas and the rapid detection of changes. One of the main problems preventing the full automation of the UAV data processing is the radiometric quality of the images (Kedzierski, Wierzbicki 2015, 2016) as well as blur caused by the movement of the platform during recording. Such defects of the image may be caused by cloud cover, strong gusts of wind, turbulence or errors committed by the pilot UAV (Kedzierski *et al.* 2014). These artefacts often make it difficult to perform visual analysis and interpretation of the data. Additionally, these defects cause errors and decrease the final accuracy of photogrammetric products. (Sieberth *et al.* 2016). Currently, new image matching algorithms are based on matching each pixel (so called dense image matching). An innovative solution for image matching techniques was the development of the Hirschmuller's global alignment algorithm named semi-global matching. (Hirschmüller 2005, 2011).

Most of the currently utilized Structure from Motion algorithms (Horn 1990) use point detectors that support the process of automatic detection of corresponding features in the images (Lowe 2004). Other commonly used detection algorithms include ASIFT and SURF. Objective quality parameters of the video sequence are extremely important in acquiring and processing of video sequences obtained from low altitudes (Kedzierski, Wierzbicki 2016). Currently, their implementation is highly automated. The most commonly used commercial packages include Trimble UAS Master Pix4D, Agisoft Photoscan whereas SURE (Wenzel 2013) and Visual SFM (Wu 2012) are good examples of open source software. Most of the quality measures (parameters) of the video sequence presented in literature are based on methods, which are sensitive to errors in the radiometric image quality. So far, no studies had been conducted on the analysis of the quality of video sequences obtained from low altitudes. Objective parameters of image and video quality play an important role in the processing of data obtained from UAV systems. In literature, most of the proposed methods for assessing the quality of a video give subjective indicators (Wu, Rao 2005).

The aim of this study is to develop metrics to assess the quality of the video image obtained from a low altitude using compact digital cameras. As part of the article we present subjective and objective indicators of video quality. The test data used in the research experiment come from UAV photogrammetric missions performed using a Trimble UX-5 in different weather and lighting conditions.

Video quality metrics

Video quality metrics are used to evaluate and process digital imagery. The most common parameters take into account the differences in brightness values of pixels between subsequent images. Objective metrics should enable the determining of characteristic image quality parameters. Depending on the parameters of the video sequences, quality metrics can be divided into three groups (Engelke, Zepernick 2007; Krasniewski 2011).

a) with a full reference – obtained by calculating the difference between the original image and the degraded;
b) the partial reference (reduced reference) – involving the comparison of certain parameters of the original and degraded signal;
c) without a reference (called: no-reference) – which depend only on the analysis of degraded signal.

In this study, we took into account quality metrics that belong to the full reference and no reference groups of indicators. Results obtained using these indicators gave results which were most correlated with the results obtained in the process of subjective and objective assessments of multimedia content. Currently, to assess the quality of a video sequence, quantitative objective metrics are used. These parameters are based on a comparison of differences between the original image frame and the image reconstructed from the video, or a compressed image (Skarbek 1998; Ohm 2012). Commonly the *Peak Signal to Noise Ratio* PSNR is used as a measure of the quality. This parameter is described by the equation:

$$PSNR = 10\log\frac{255^2 N^2}{\sum_i e_i^2}\left[dB\right], \tag{1}$$

where:

255 – dynamic range of the signal,

N – number of image points,

e_i – the difference between point *i* of original and decoded image.

To assess the quality of a video, the VQM metric (Video Quality Metric) (Chikkerur *et al.* 2011) developed by the ITS (Institute for Telecommunication Sciences) is also used. According to the authors of the index, it allows for an objective assessment of the video quality to be made. This metric includes the distortions of video signal such as: blurring, image blocking effect, deformation of contours and combinations thereof. Another frequently used metrics to assess the quality of the video is the MSE index (Mean Square Error), where the value of the mean square error for each pixel of the image (frame) is calculated (Bhat *et al.* 2010).

For calculating the absolute metric is used Bluring Metric, which measures changes in the brightness of each pixel's neighbourhood. The higher the value of this metric, the better the image quality is (Marziliano *et al.* 2002). Another metric that is relevant to the assessment of the absolute video quality is the Blocking Metric, which describes interlocking pixels. This distortion results from the image processing method in a system using the DCT transform, which processes the image pixel blocks, the size of which is usually a multiple of 8. This metric exposes degradation of the video quality for frames of similar colour and brightness. The metric determines the differences for contrasts and colours within an 8×8 pixel matrix. A value of 0 means no distortion, the higher the value, the higher the distortion and thus lower quality of video sequences (Marziliano *et al.* 2002). On the other hand, the Brightness Flicking Metric describes the distortion characterized by flicking between adjacent frames. The value of this metric is the mean absolute difference of the brightness of all the pixels of the video frame compared to the previous frame. A higher value means greater flickering (Madhusudhan, Pais 2007). To assess the quality of the video signal, the SSIM (Structural similarity) index is often used. It takes into account three types of distortions in the image (Krasniewski 2011): the image luminance, contrast, and structure. Assuming that $x = \{x_i \mid i = 1,2,...,N\}$ is the original (source) signal, and $y = \{y_i \mid i = 1,2,...,N\}$ is the distorted signal with, the SSIM value can be determined based on the following relation (Wang *et al.* 2004; Wang 2006):

$$SSIM = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}, \tag{2}$$

where constant values:

μ_x^2, μ_y^2 – mean value,

σ_x^2, σ_y^2 – variance,

σ_{xy}^2 – covariance x and y;

$C_1 = 0.01 \cdot L$; $C_2 = 0.03 \cdot L$.

This index ranges from 0 to 1. The result of applying the SSIM for the parts of the image defined by an N×N pixel mask, is a map of the image quality with a resolution equal to that of the image decreased by N-1 lines and N-1 columns. Authors of this index (Wang *et al.* 2004) recommend the use of a two-dimensional Gaussian window, 11×11 pixels in size.

Other video quality metrics

Other video quality metrics include indicators belonging to the reduced reference group. Among these is the MPQM index, which is based on a perceptual evaluation of the video quality. The principle of its operation is based on the distribution of individual video channels to simulated ranges of visual perception for humans based on the HSV space. MPQM index does not account for chrominance. At the beginning, colour components are converted to RGB values that have a linear luminance distribution. Then, the RGB values are converted to coordinate values of luminance (B / W), the red-green channel (R / G) and blue-yellow (B / Y) (Wang *et al.* 2004). An important metric of the video quality is also the NQM (*Noise Quality Measure*) measure (Damera-Venkata *et al.* 2000). A quality metric based on the two Measures (NQM and DM) is yet to be define (Wang 2006) Another quality measure is the CVQE (continuous video quality evaluation) parameter that is based on a multi-channel decomposition using a discrete Fourier transform. This metric is used mainly for video compression standard H.263. (Hemami, Masry 2005). Another metric is the TDNN ratio, that includes chromatic components and Krauskopf's achromatic colour space component (Le Callet *et al.* 2005). Another metric is based on the idea of enhancing available parameters related to the size and type of the video frames, with motion descriptors. This metric is used mostly for MPEG-4 file formats (Lotfallah *et al.* 2006). Another group of parameters to assess video quality are non-reference NR methods, that are based on the analysis of only the degraded signal. Non-reference methods can be divided into groups (Engelke, Zepernick 2007): metrics of a single feature, eg. blocking, blurring (Tan, Ghanbari 2000; Wu, Yuen 1997), metrics combining features and structural information (Coudoux *et al.* 2001), metrics taking into account the parameter settings of the codec (Yang *et al.* 2007), metrics using methods such data hiding (Esen, Alatan 2011). Among the metrics of a single feature, we can distinguish the following: metrics that are based on statistical measurements of the frequency distribution using a kurtosis method (Caramma *et al.* 1999; Farias *et al.* 2002) for the index measuring the degree of degradation of video coding MPEG-2 (Caramma *et al.* 1999). Another example is the MAV metric (mean annoyance values), focusing on three different artefacts: blocking, blurring and its noisiness (Farias *et al.* 2002; Cavallaro, Winkler 2004; Ries *et al.* 2005). The above methods of evaluating the quality of video sequences are characterized by relatively simple computational algorithms. However, these algorithms are often based on the determination of the degree of similarity between the original video sequence and degraded. Often, averaged measures of the video quality may not be sufficient, whereas local indicators and their interpretation are strongly dependent on the texture mapped on the scene (eg. built-up area, wooded area) and the impact of individual structures and their components. Therefore, the evaluation of the quality of the images obtained from low altitudes is a difficult issue that requires the development of an objective indicator of the video quality in order to assess the predicted accuracy of modern photogrammetric products.

The research methods and experiment. Results and discussion

Video data in the RGB and near-infrared (NIR) ranges were obtained using a Trimble UX-5 UAV equipped with one of two cameras: the Sony NEX5R (RGB) and the Sony NEX5T with a filter IR (NIR). The missions were conducted in July 2015 near the town of Owsianka located 60 kilometres north-east of Warsaw (Poland). The terrain was flat, with a few scattered trees and shrubs and a small number of buildings. The second measurement campaign was performed in March 2016 in Tylicz (Poland).

Video sequences were recorded using a super bright Voigtlander lens with a focal length of 15 mm and a maximum aperture F4.5 (Kedzierski *et al.* 2014). Video sequences were recorded in AVCHD format with a resolution of 1920×1080 pixels and compression H.264 at 25 frames/sec.

The weather and lighting conditions for the flight missions carried out in the first measurement campaign were favourable. The sky was clear and there was little cloud cover. The average intensity of light was approx. 10 000 lux. In the second measurement campaign the weather conditions were worse – rather cloudy, sometimes noticeable haze occurred. The average light intensity amounted to approx. 3 000 lux.

Research was performed on video signals obtained from the two measurement campaigns. Comparative analyses of the video signals were made in the MSU Video Quality Measurement Tool software (Vatolin *et al.* 2009). For a comparative analysis of recorded video, the PSNR, SSIM and three objective quality indicators (no-reference metrics) were used.

Comparative analysis of RGB video sequences – 100 m and 300 m altitude – the first measurement campaign

For the first comparative analysis, video data obtained in the first measurement campaign was used. Video data was acquired from an altitude of 100 m 300 m with similar lighting conditions. Both sets of video data were recorded with a resolution of 1920×1080 pixels, a H.264 compression and YUV420p subsampling. Results of consecutive analyses with different quality metrics are presented in Figures 1–5.

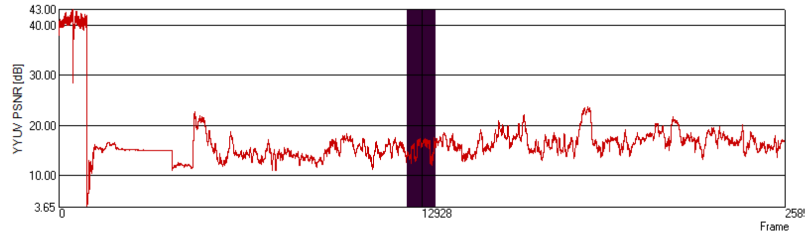

Fig. 1. Comparison of video signals for altitudes: 100 m and 300 m – PSNR index

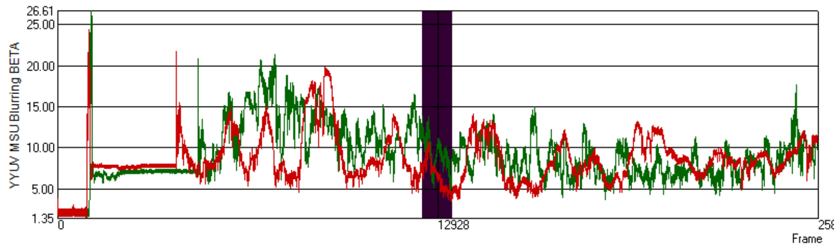

Fig. 2. Comparison of video signals for altitudes: 100 m (green plot) and 300 m (red plot). MSU Bluring Metric index

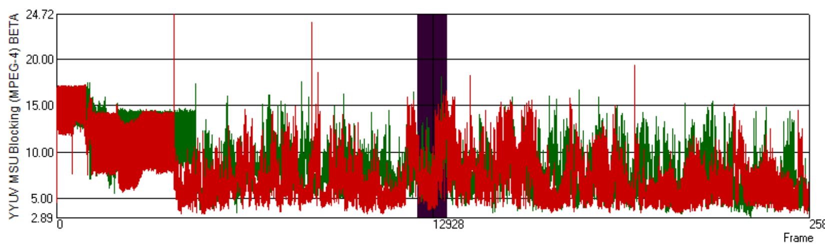

Fig. 3. Comparison of video signals for altitudes: 100 m (green plot) and 300 m (red plot). MSU Blocking Metric (MPEG-4) index

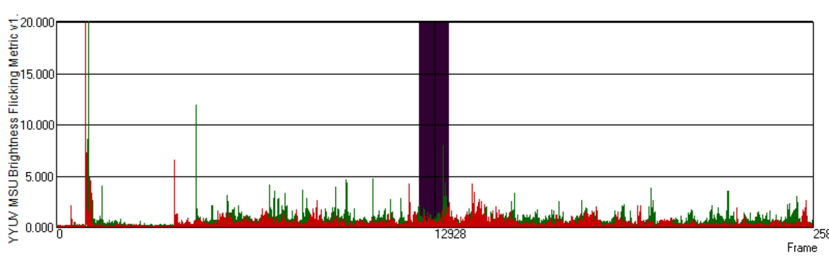

Fig. 4. Comparison of video signals for altitudes: 100 m (green plot) and 300 m (red plot). MSU Brightness Flicking Metric index

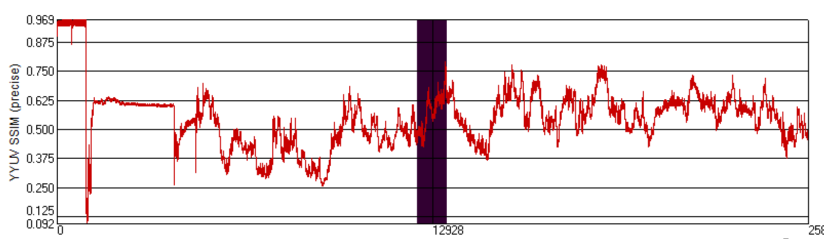

Fig. 5. Comparison of video signals for altitudes: 100 m and 300 m – SSIM Y-YUV index

For the three RGB components (25861 video frames recorded at the altitude of 100 m and 300 m) comparative analyses have been done. The values of the metrics were calculated in the YUV model for the luminance (Y) component. In the first study video frames were compared with each other using the relative PSNR and SSIM metrics and three absolute metrics (non-reference metrics): Bluring Metric, Blocking Metric and Brightness Flicking.

Research showed (Figs 1–5) that data acquired at 100 m has better radiometric quality. Only in the case of the Brightness Flicking metric analysis these results were different. The metrics values presented in Table 1 suggest the presence of flicker, that could be caused by a sudden change of lighting conditions.

Table 1. Video sequences quality indices – analysis results for video sequences acquired from 100 m and 300 m

Metrics-mean value	altitude	
	RGB 100m	RGB 300m
PSNR [dB]	15.298	
MSU Bluring Metric	9.030	8.396
MSU Blocking Metric	8.407	7.594
MSU Brightness Flicking	0.301	0.207
SSIM Y-YUV	0.548	

The obtained value of the PSNR ratio indicates that data acquired at the 300 m altitude are affected by much more noise. This is a relative metric, so both video sequences cannot be evaluated unambiguously. Therefore, the further three studies were performed using relative metrics. The video signal obtained at 100 m altitude was characterized by a 16% better radiometric quality. For both samples the value of the MSU Brightness Flicking index was much smaller than 1, which also indicates good radiometric quality. Similar results also were obtained with respect to the relative SSIM metric.

Comparative analysis of RGB and NIR video sequences – 150 m altitude – the second measurement campaign

For the three RGB components, an analysis of all 25870 video frames recorded at the altitude of 150 m had been done. The RGB and NIR video data was compared. Like previously, the videos were recorded with 1920×1080 pixels resolution, a H.264 compression and YUV420p subsampling. Figures 6–10 present the results.

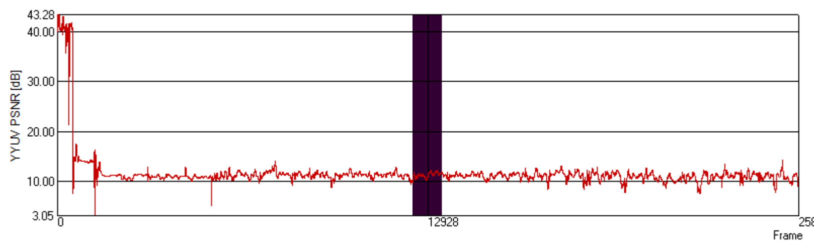

Fig. 6. Comparison of video signals for 150 m altitude for RGB and NIR. PSNR index

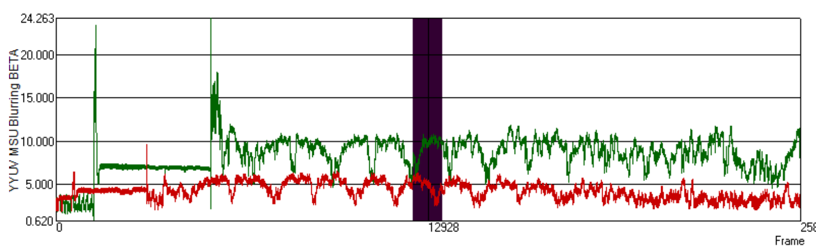

Fig. 7. Comparison of video signals for 150 m altitude for RGB (green plot) and NIR (red plot). MSU Bluring Metric index

For the three RGB components, 25870 video frames recorded at the altitude of 150 m were analyzed. As in the previous experiment, values of the metrics were calculated for the YUV model for the luminance (Y) component. Also the same quality metrics – two relative and three absolute, were applied. On the basis of these experiments, it was observed that the calculated values of the quality parameters suggest better radiometric quality of the RGB images (Figs 6–9). As in the previous experiment, the analysis that involves the Brightness Flicking metric gave worse results for RGB compared to the NIR imagery. The obtained results (Table 2) show that there is evident flickering occurring on the images, which could have been caused by changes to the lighting conditions during data acquisition.

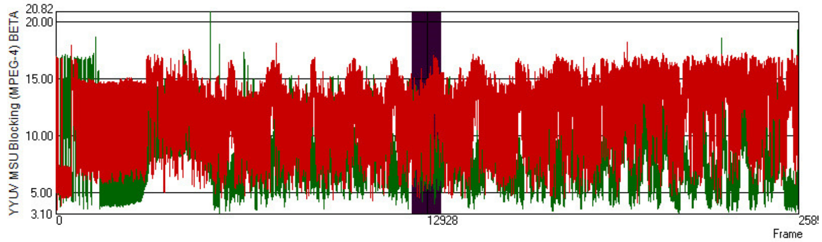

Fig. 8. Comparison of video signals for 150 m altitude for RGB (green plot) and NIR (red plot). MSU Blocking Metric. (MPEG-4) index

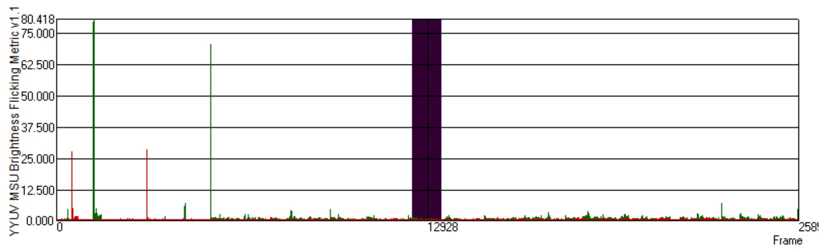

Fig. 9. Comparison of video signals for 150 m altitude for RGB (green plot) and NIR (red plot). MSU Brightness Flicking Metric index

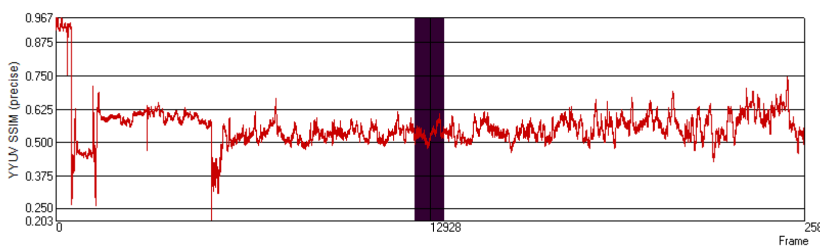

Fig. 10. Comparison of video signals for 150 m altitude for RGB and NIR for SIM Y-YUV index

Table 2. Video sequences quality indices– second measurement campaign

Metrics – mean value	altitude	
	RGB 150 m	NIR 150 m
PSNR [dB]	10.968	
MSU Bluring Metric	8.175	4.056
MSU Blocking Metric	8.184	11.838
MSU Brightness Flicking	0.219	0.097
SSIM Y-YUV	0.556	

With respect to the obtained value of the PSNR ratio (10.968 [dB]), it can be concluded, that the images obtained in the NIR range have greater noise in comparison to the video sequence recorded in the RGB channels. The noise is, however, lower by 28% compared to RGB data obtained at the 300 m altitude. As in the previous experiment, due to the fact that PSNR is a relative metric, it cannot be associated with quality of a single movie. As previously, three relative metrics were used. On this basis, it was observed that the radiometric quality of RGB image was better by 20%. Only in the case of MSU Brightness Flicking metric, it was found that the RGB video sequences were characterized by a 50% higher image flickering frequency in comparison to the NIR video. Nevertheless, in both cases the value of the MSU Brightness Flicking index was much less than 1. Similar results were also observed with respect to the relative SSIM metric.

Conclusions

In the article the possibility of using UAV technology to acquire video data from low altitudes was presented. Two subjective parameters: PSNR and SSIM, and three non-reference quality metrics were used for comparative analyses.

The experiments showed that subjective metrics allow for only a partial, at best, evaluation of the radiometric quality of video sequences. The relative metrics: MSU Bluring Metric, Metric Blocking MSU and MSU Brightness Flicking were seen to be the better parameters for assessing image quality. The study showed that the selected quality indicators enable an initial assessment of the video quality as a function of altitude and spectral range.

On the basis of these experiments it was found, that video sequences acquired in similar lighting conditions, but at different altitudes (100 m and 300 m) differ from each other in radiometric quality. Based on the results obtained in the second measurement campaign it was found that video sequences acquired at the same altitude (150 m), but in different spectral bands (RGB and NIR) also differ from each other in radiometric quality. Better results were obtained for RGB video sequences.

Future research will focus on solutions aimed at the application of a UAV video sequence in generating an orthophotomosaic.

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