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Solution for remote real-time visual expertise of agricultural objects

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Abstract. In recent years automated image and video analyses of plants and animals have become important techniques in Precision Agriculture for the detection of anomalies in development. Unlikely, machine learning (i.e., artificial neural networks, support vector machine, and other relevant techniques) are not always able to support decision making. Nevertheless, experts can use these techniques for developing more precise solutions and analysis approaches. It is labour-intensive and time-consuming for the experts to continuously visit the production sites to make direct on-site observations. Therefore, videos from the site need to be made available for remote viewing and analysis. In some cases it is also essential to monitor different parts of objects in agriculture and animal farming (e.g., bottom of the plants, stomach of the animal, etc.) which are difficult to access in standard recording procedures. One possible solution for the farmer is the use of a portable camera with real-streaming option rather than a stationary camera.
The aim of this paper is the proposition of a solution for real-time video streaming of agricultural objects (plants and/or animals) for remote expert evaluation and diagnosis. The proposed system is based on a Raspberry Pi 3, which is used to transfer the video from the attached camera to the YouTube streaming service. Users will be able to watch the video stream from the YouTube service on any device that has a web browser. Several cameras (USB, and Raspberry Pi camera) and video resolutions (from 480p till 1,080p) are compared and analysed, to find the best option, taking into account video quality, frame rates, and latency. Energy consumption of the whole system is evaluated and for the chosen solution it is 645 mA.

Key words: precision agriculture, video streaming, visual observations.

INTRODUCTION

Precision agriculture and its sub-branches, such as Precision Livestock farming and Precision Beekeeping (Zacepins et al., 2015) is based on detailed information on the status of agricultural objects using various technologies (Terry 2006; Wrest 2009; Abassi et al. 2014). Agricultural objects can be an individual plant, a set of plants or animals. Crop and animal protection, plant watering and fertilization processes need frequent updates in data, which afterwards is analysed and a decision is proposed to the farmer.

In current years automated image and video analyses of plants or animals for detection of anomalies in their development have become an important and emerging techniques in Precision Agriculture (Vranken & Berckmans 2017). The technology (hardware, camera and periphery) is relatively cheap and non-invasive, which facilitate the collection of more frequent data over longer time periods. The use of cameras and automated image processing techniques, makes it possible to obtain information on the behaviour of animals, analyse the data and detect possible deviations from expected values (Kashiha et al., 2013). The technology of monitoring animals by image processing is not new and already have been widely applied by many scientists and practitioners (Aydin et al., 2010). For example, broilers can be monitored by image analysis to estimate daily body weight changes (De Wet et al., 2003), to assess the chicken activity (Aydin et al., 2010), to investigate possibility of detecting leg disorders in broiler chickens (Kristensen & Cornou, 2011). Also image processing is widely used for pig monitoring (Tillett et al., 1997; Shao et al., 1998; Nasirahmadi et al., 2016; Nasirahmadi et al., 2017) and for cow wellness monitoring (Cangar et al., 2008).

It should be mentioned that image processing could be used not only for animal monitoring, but also for the plants. Image processing is a promising tool for non-destructive analysis of biological objects, and has been widely used in botanical research and practical agriculture (Ibaraki & Dutta Gupta 2010; Yadav et al., 2010; Dutta Gupta et al., 2012; Vesali et al., 2015; Mahlein 2016; Bodner et al., 2017; Vesali et al., 2017).

Unfortunately, modern information and communication technologies (ICT), like machine learning, satellite navigation, sensor network, grid computing, ubiquitous computing and other relevant technologies supporting the domain for improved monitoring and decision making capabilities (Shaikh, 2009) are not always able to support adequate and fast decision making. Nevertheless, experts can be more precise in analysing scenarios and supporting decisions, particularly when analysing images or videos. In commercial livestock houses as well as greenhouses, image analysis for behaviour/growth classification becomes more complex. Lighting, camera characteristics, background and the test subjects' traits all influence the ability of the system to detect or recognise the subject and determine its features accurately.

It is not always economically feasible for experts to visit geographically remote production sites to make on-site observations, so there is a need for making videos from the site available for remote viewing and analysis. Furthermore, it is necessary to provide videos from different angles and perspectives (such as bottom of the plants leaves, abdomen of the animal, etc.). Therefore, usage of automated recording is not always possible. Additionally, experts require on-demand details on the observed object. Thus, bi-directional real-time communication between the farmer and the expert is mandatory, as pre-recorded videos are not always suitable for precise diagnosis.

The aim of this paper is to propose a solution for real-time video streaming of agricultural objects (plants and/or animals) for remote expert evaluation and diagnosis. The proposed system is based on a Raspberry Pi 3, which is used to transfer the video from an attached camera to the YouTube streaming service. The system can be used by farm workers to transmit real-time video for remote expert analysis.

DEVELOPED SOLUTION BASED ON RASPBERRY PI

The proposed system is based on a Raspberry Pi 3, which is a replacement for the Raspberry Pi 2 Model B, released in February 2016. The Raspberry Pi is a credit card sized single board computer developed by the Raspberry Pi Foundation, United Kingdom. The board is a miniature PC, packs extreme computing power and is capable to develop sophisticated projects. The Raspberry Pi is well suited to perform a multitude of computing tasks and for interfacing various types of devices via GPIO (Nayyar & Puri 2015). The key specification of the Raspberry Pi 3 is: Quad Core 1.2GHz Broadcom BCM2837 64bit CPU, 1GB RAM, BCM43438 wireless LAN and Bluetooth Low Energy (BLE) on board, 4 USB 2 ports, CSI (camera serial interface) camera port for connecting a Raspberry Pi camera. Due to its small dimensions, low weight and power consumption it is suitable for the development of wearable devices and solutions.

The proposed system architecture is shown in Fig. 1. The external web camera is connected to the Raspberry Pi USB port, and is used to capture high definition video (resolution 1,080p). The system automatically delivers the video stream to YouTube live service using the wireless transmitting method. A Raspberry Pi is connected to external Wi-Fi router. The intended users (experts) are able to watch the video stream from the YouTube service on any supported device.

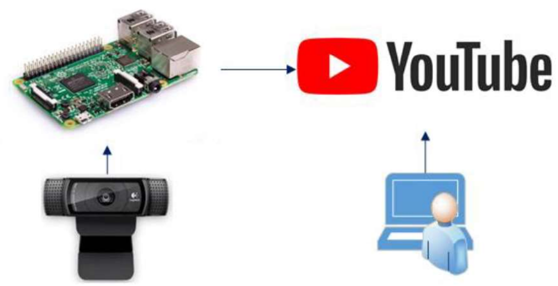

Figure 1. Schematic view of the developed system architecture.

In this study the YouTube service was used for real-time video streaming as it can be considered as major video stream service nowadays. YouTube was started as a project with the aim to remove the technical barriers to share videos online. YouTube continues working on further optimization of their video streaming service.

YouTube is not the only service to choose from. For live video streaming, there are several services from different providers. Netflix open connect (*https://openconnect.netflix.com/)* - Netflix works together with NGINX, this project wants to improve the load balancing for video streaming over the whole network. Another service is WOWZA (http://www.wowza.com/), which provides video streaming for companies and universities.

Main advantage of the YouTube service is, that infrastructure solution is already in place: for the described project there is no need for a special solution for video record archiving, which is also valuable for agricultural experts.

To stream real-time video on YouTube it is necessary to use RTMP (real time messaging protocol), which was originally developed for streaming data between a video player and a server. RTMP is encapsulated in HTTP to traverse firewalls. RTMP has more video player options compared to normal HTTP, thus giving the user a better experience. A disadvantage compared to normal HTTP is that it is sensitive for data spikes. These data spikes can result in an overload of the buffer, which in turn can lead to a stop in the video playing.

One more requirement of the YouTube service is that streamed videos should be encoded in the H.264 format. Not every web camera provides raw access to this format by hardware encoding, so there might be a need to transcode the camera output to H.264, and this process is consuming significant CPU resources.

To activate the option for real-time streaming it is necessary to sign up for the YouTube service. Then after log in and account confirmation, it is required to open the Creator Studio and choose the Live Streaming option. Two main parameters for streaming are: Server URL (for example, *rtmp://a.rtmp.youtube.com/live2*) and unique stream name/key (in format like xxxx-xxxx-xxxx-xxxx). When this information is known it is possible to start live streaming from a Raspberry Pi using the following Linux command:

```
ffmpeg -re -ar 44100 -ac 2 -acodec pcm_s16le -f s16le -i /dev/zero \
         -input_format h264 -video_size 1,920x1,080 -i /dev/video0 \
         -vcodec copy -acodec aac -ab 128k \
         -f flv -movflags faststart \
         rtmp://a.rtmp.youtube.com/live2/xxxx-xxxx-xxxx-xxxx
```

In this research FFmpeg is used which is a free software project that produces libraries and programs for handling multimedia data. It is possible to configure audio and video inputs, transcoding options and output parameters.

The system components with their approximate unit prices, which were available for the authors, are summarized (Table 1) below.

Table 1. System components with approximate unit price used in this study

Nr.	Name of the component	Quantity (pieces)	Price per piece (EUR)
1	Raspberry Pi 3 (including 8GB SD card)	1	44.00
2	Raspberry Pi 3 case	1	10.00
3	Logitech c920 web camera	1	84.00
4	Power Bank (Adata P12500D, capacity 12500mAh)	1	18.00
		Total	**156.00**

COMPARISON OF DIFFERENT CAMERAS

The described solution was developed iteratively: the authors tested different web cameras and output modes. The results of the conducted experiments are summarised below.

The Raspberry Pi 3 was set up with the Linux operating system *Raspbian* (release: 9.1). No additional configurations were performed, to reduce resource consumption. During inactive periods (*idling*), the device consumed approximately 79 MB of RAM with a load average of: 0.23, 0.24, 0.2 (average values during 1, 5 and 15 minute periods, respectively) as provided by the *htop* utility. In such conditions the Raspberry Pi consumed approximately 280 mA. Testing was conducted in the laboratory with microclimate conditions with an ambient temperature of 22 °C and a relative humidity of 30%. Wi-Fi connection speeds were as follows: download speed up to 43 MBps and upload speed up to 91 MBps. As the Raspberry Pi itself is a well exposed naked circuit board which cannot be used without any extra casing for agriculture related surveys the authors used standard a plastic casing with a radiator for CPU.

To test and compare resource and power consumption (crucial, when powering from battery pack) a separate operating system (DietPi) was installed. DietPi is a lightweight operating system for single board computers (http://dietpi.com/#noAction).

The core installation of DietPi was supplemented with the following software: ffmpeg, Dropbear SSH server. During inactive periods, approximately 38 MB of RAM was used with a load average of: 0.07, 0.07, 0.03. Tests proved that there was no significant difference regarding power consumption – it was constant (approx. 280 mA). To reduce the power consumption, the HDMI and activity LED of the Raspberry Pi 3 were disabled (as described by Geerling (2017). This resulted in a current reduction by 30 mA.

The very first attempt was to use the Raspberry Pi camera module, which is capable to take HD videos as well as still photos, for video capturing. The Raspberry Pi camera has effective resolution of 5 Mega-Pixel and supports video recording at: 1080@30fps, 720p@60fps and Vga@90fps. It can be connected to the Raspberry Pi via a CSI port (Nayyar & Puri 2015).

In the second phase the authors used a Logitech HD PRO webcam C920 (*https://www.logitech.com/en-us/product/hd-pro-webcam-c920#specification-tabular)* as external USB web camera. The main features of importance for the research were: full HD video recording (up to 1,920 x 1,080 pixels) and H.264 video hardware compression. Camera output formats can be verified in the Linux system using the command below:

```
$ v4l2-ctl --list-formats -d /dev/video1
ioctl: VIDIOC_ENUM_FMT
Index       : 0
Type        : Video Capture
Pixel Format: 'YUYV'
Name        : YUYV 4:2:2

Index       : 1
Type        : Video Capture
Pixel Format: 'H264' (compressed)
Name        : H.264

Index       : 2
Type        : Video Capture
Pixel Format: 'MJPG' (compressed)
Name        : Motion-JPEG
```

Logitech C920 camera output is available in several formats: YUYV (raw), H.264 and MJPG. It is important, that the camera has built-in hardware compression to H.264 that is accepted by YouTube directly. Other formats should be transcoded to H.264 using additional software. It should be taken into account that the camera can have hardware encoding H.264 in the specification, but sometimes it is encapsulated in MJPG format and can be used only by specific software, like Skype and cannot be transmitted to YouTube directly (e.g. Logitech c925e web camera).

A comparison of different possible scenarios using the above-mentioned cameras and different video formats was conducted. Several system parameters were compared, such as: energy consumption, CPU load, amount of used RAM, consumed power by the

Raspberry Pi, latency to broadcaster on YouTube (from viewer's perspective) and video quality.

Video quality was evaluated in a testing environment with room lighting conditions (day lights): a printed document with 10 text rows written in different font sizes, starting from 26 pt till 8 pt was placed in front of a camera with a distance of 50 cm. Image quality is estimated by the smallest text row, that is easy human readable on resulting video stream.

For real latency evaluation a real time clock was recorded, and it was compared with the time on the local PC. The current consumed by the Raspberry was measured using a KW203 USB Current and Voltage Detector, with a measurement range for voltage of: DC 3.2-10 V; and current: DC 0-3 A (accuracy 1 percent (about 2 digits)).

For the Raspberry Pi CPU and RAM loads the Linux system utility (`$ ps -C ffmpeg -o %cpu,%mem,cmd`) was used. The stream bitrate was reported by ffmpeg software itself.

Conducting various experiments the authors strived to find the possible maximal video resolution that can be streamed from Raspberry Pi 3 using software and hardware transcoding.

Due to the YouTube service requirement necessity for the existence of an audio channel in a video stream the authors faked the audio input by interpreting the /dev/zero device output as audio stream.

The results of the experiments are summarised below in Table 2.

Table 2. Comparison of different streaming scenarios

Resolution	Format	CPU, %	RAM, %	Power, mA	Lat, s	R.lat, s	Remarks	Quality	Score	Bitrate, kbps
	Raspberry Pi camera hardware encoding									
640 x 480	H.264	15.1	1.4	335	1.6	14	Partial FOV, Pixel bins	1	Yellow	1,350
720 p	H.264	17.3	1.6	380	1.7	10	Pixel bins	2	Green	2,300
1,640 x 922	H.264	19.7	1.6	400	1.5	7	Full width	2	Yellow	3,900
1,080p	H.264	21.9	1.7	425	1.9	6	Partial FOV	3	Green	5,000
	Logitech c920 software encoding									
640 x 400	yuv422	223.0	8.2	565	3.2	13	5 fps	1	Yellow	550
1,280 x 800	yuv422	338.0	25.1	620	7.5	57	1 fps	4–5	Red	1,500
1,280 x 800	yuv422	194.0	13.1	550	2.29	10	5fps, ultrafast	4–5	Green	31,290
1,280 x 800	yuv422	189.0	17.0	545	2.8	6	5fps, ultrafast,crf=12	5–6	Green	19,190
1,280 x 800	yuv422	161.0	17.1	515	3.65	12	5fps, ultrafast,crf=17	5–6	Green	11,100
	Logitech c920 hardware encoding									
1,080 p	H.264	18.3	15.9	645	2.1	4	-	8–9	Green	3,030

During the experiments with the Raspberry Pi camera, the highest achieved quality score was 3, which is not acceptable for detailed observation of agricultural objects. The following command for the video streaming utilizing the Raspberry camera was used during the experiment:

```
raspivid -o - -t 0 -vf -hf -w 1920 -h 1,080 -fps 30 -md 1 -n -fli 50hz | \
ffmpeg -re -ar 44100 -ac 2 -acodec pcm_s16le -f s16le -ac 2 -i /dev/zero \
          -input_format h264 -i - \
          -vcodec copy \
          -acodec aac -ab 128k \
          -f flv -movflags faststart \
          rtmp://a.rtmp.youtube.com/live2/xxxx-xxxx-xxxx-xxxx
```

Different camera modes were selected by changing –w, -h and –md parameters of raspivid command.

It was observed, that increasing the video quality, there are small increase in CPU usage and in Raspberry power consumption. The amount of RAM stays the same. Real latency decreased from 14 s to 6 s, this can be explained by the fact, that in lower video quality there is pixel binning method applied, but in higher quality pixels are mapped directly to camera pixel sensors. In several high-resolution modes the camera produces partial FOV (field of view) images, which are not always suitable for agricultural object observations.

During the experiments with the external web camera and software video encoding, the highest achieved quality score was 5–6. The main limitation of software encoding is the enormous CPU usage, which limits the highest resolution to be used for video streaming.

```
ffmpeg \
    -re -ar 44100 -ac 2 -acodec pcm_s16le -f s16le -ac 2 -i /dev/zero \
    -video_size 1280x800 -pix_fmt yuv422p -r 1 -i /dev/video0 \
    -acodec aac -ab 128k \
    -vcodec libx264 -g 8 -profile:v high422 -level 4.0 -bf 2 -coder 1 \
    -f flv -movflags faststart \
    rtmp://a.rtmp.youtube.com/live2/xxxx-xxxx-xxxx-xxxx
```

Different software encoding configuration parameters were selected by changing `-profile`, `-level`, `-bf` and `-crf` parameters of `ffmpeg` command.

The best results for software encoding can be achieved with parameters producing video streams with high bitrates and lower image compression, which in turn uses less CPU power. In this case the data transmission channel becomes the limiter for better quality streaming. The authors tested bitrates up to 60 Mbit which did not achieve significant quality improvement.

During the experiments with the external web camera and H.264 hardware video encoding, the highest achieved quality score was 8–9 and it was considered to be the best solution for real time video streaming. The streaming bitrate was about 3,030 kbps, Raspberry CPU usage and RAM were also relatively low at 18.3% and 15.9% respectively. The average power consumption was 645 mA. The observed real latency was 4s, which is acceptable for the mentioned task.

Using the provided power bank with a capacity of 12,500 mAh the developed system would be able to operate more than 13 hours. The battery life or capacity can be calculated from the input current rating of the battery and the load current of the circuit. The calculation to find the capacity of the battery can be mathematically derived from the following formula (1):

$$BL = \frac{BC}{LC} \cdot 0.7, \quad (1)$$

where BL – Battery Life, BC – Battery Capacity, LC – Load Current, the factor of 0.7 makes allowances for external factors, which can affect battery life.

So in case of this study Battery Life = 13.57 Hours (2).

$$BL = \frac{12,500}{645} \cdot 0.7 \quad (2)$$

That system life is extended enough for remote visual expertise of needed agricultural objects.

Usually farms are located outside the urban areas, where Wi-Fi connection might not be available. Therefore, an additional test was carried out to identify if the system can operate using mobile internet connections. It was concluded that 3G technology is not suitable for real-time video streaming. However, using the 4G technology system performed well.

As Raspberry Pi is used with a plastic case in real environments, the CPU temperature during streaming was measured. As in practice the video is streamed for remote experts, one stream episode cannot not be longer than 30 minutes. The observed CPU temperature was starting from 25 °C in idle state, increased by 4 °C in the first ten minutes, then increased by 2 °C in next ten minutes. At the final time of 30 streaming minutes the CPU temperature was still 31 °C. Measurements of the CPU temperature conducted using a infrared thermometer Standard ST-8811.

CONCLUSIONS

Continuous and real time monitoring of agricultural objects has become a common tool not only for research but also for practical agriculture and livestock farming.

Application of video observation systems has also become widely used in both precision agriculture and farming systems. Unfortunately, not every task can be solved by automated and fixed camera systems. There are cases, when it is necessary to record video manually by changing the position of the cameras.

Proposed system can be used in various scenarios, when remote expert consultation is needed.

Comparing different scenarios and camera configurations, the results showed that usage of an external web camera with built-in H.264 encoding is the best option, despite the price of such camera (up to 100 EUR).

Usage of video software encoding on a Raspberry Pi is challenging due to limited CPU power, which needs to be considered for larger scale monitoring.

In the future, it is planned to test the described proof of concept in real agricultural situation, with different environmental conditions (e.g., climate changes, lighting situations for camera).

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