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Amir S. Bernat, Frank J. Bolton, Reuven Weiser, David Levitz, "Cloud-based processing of multi-spectral imaging data," Proc. SPIE 10055, Optics and Biophotonics in Low-Resource Settings III, 1005505 (3 March 2017); doi: 10.1117/12.2252189

SPIE.

Event: SPIE BiOS, 2017, San Francisco, California, United States

Cloud-based processing of multi-spectral imaging data

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ABSTRACT

Multispectral imaging holds great promise as a non-contact tool for the assessment of tissue composition. Performing multi-spectral imaging on a hand held mobile device would allow to bring this technology and with it knowledge to low resource settings to provide a state of the art classification of tissue health. This modality however produces considerably larger data sets than white light imaging and requires preliminary image analysis for it to be used. The data then needs to be analyzed and logged, while not requiring too much of the system resource or a long computation time and battery use by the end point device. Cloud environments were designed to allow offloading of those problems by allowing end point devices (smartphones) to offload computationally hard tasks. For this end we present a method where the a hand held device based around a smartphone captures a multi-spectral dataset in a movie file format (mp4) and compare it to other image format in size, noise and correctness. We present the cloud configuration used for segmenting images to frames where they can later be used for further analysis.

Keywords: Spectral analysis, imaging, cloud computing

1. INTRODUCTION

Cervical cancer is the leading cause of cancer death for women in low resource settings¹, where approximately 85% of the world's population lives. In low resource settings, the health system does not have the necessary resources to support standard of care cervical cancer screening and follow up colposcopy, biopsy, and if necessary therapy². The key bottleneck in many of these health systems is in the colposcopy and biopsy step, which occurs because of a general shortage in the number of available gynecologists, as well as a lack of resources and pathologists to interpret histopathology results. An optical biopsy at the point of care would increase access for patients and allows the health system to provide standard of care medicine without overburdening the system^{3,4}.

In developed health systems, the follow up test to an abnormal Pap smear or HPV DNA primary screen is colposcopy, a procedure in which a clinician visually examines the cervix and external genitalia using a colposcope, a bright-field imaging device positioned outside the patient's body^{5,6}. The clinician then uses several tests to look for pathology in cervical tissue. Excisional biopsies are then used to collect tissue samples for further examination from areas of suspected pathology.

Multi-spectral imaging is a promising imaging method that augments traditional white light colposcopy^{4,7,8}. Here, the tissue is illuminated by different wavelengths of light, capturing reflectance image data at each wavelength. The wavelengths form a spectra that varies as a function of position. Fitting the spectra to a theoretical model, it is possible to quantitatively measure absorption and scattering in the tissue⁴. The absorption can be broken up to contributions from blood, water, and oxy- and deoxy-hemoglobin. Scattering can be broken down into the Mie and Rayleigh components^{4,7,9}. Absorption and scattering measurements are quantitative measures of the green filter and acetowhitening tests.

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One major challenge with measuring scattering and absorption properties of tissue using multi-spectral imaging is that the technology is very computationally intensive. This results in 2 alternatives to processing the data – on the local device, or in a cloud-based server. But integrating the necessary hardware into a compact form factor necessary for low resource settings can become rather challenging when trying to scale. In contrast, a cloud-based solution is advantageous because it is lower in cost, lower in hardware complexity, and offers sufficient computational power. The data flow in such an implementation is presented in Fig. 1.

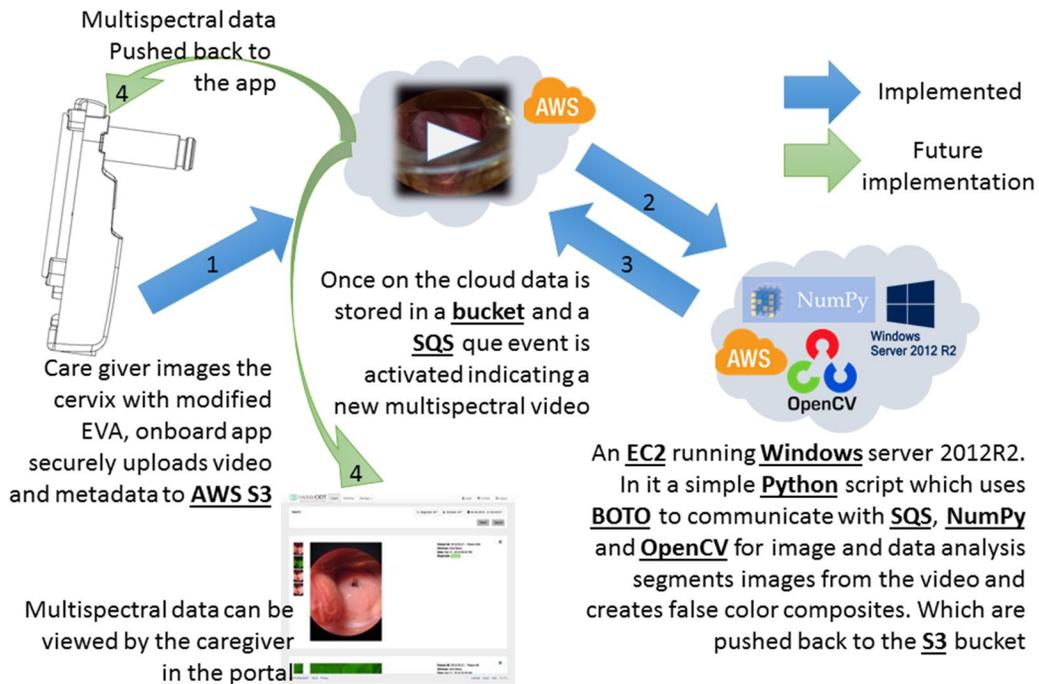


Fig. 1: General flow of data from multi-spectral imaging device to cloud servers and back to device. Data from the imaging device uploads (1) the video and metadata to an S3 bucket on AWS, initiating an SQS que event (2). An EC2 instance running Windows is processes the data using a script in Python, and returns the output back to the S3 bucket (3) which pushes the data to the MobileODT and/or the user (4).

There are many ways in which multi – spectral data can be analyzed, the most computationally expensive and requiring the most accurate measurements are of the scattering and absorption as detailed previously, stepping stones in that endeavor are data driven methods¹⁰ where relation between wavelengths of healthy and alignment tissue is compared. At this moment several commercial devices are available in the market where a LEDs and color cameras are used to create a real time false color image¹¹ which highlights specific tissue features.

The key step in efficient offloading to cloud processing is transferring the data to the cloud for analysis. Specifically, the use of a compression step is where the key tradeoff occurs¹². More compression allows for reduction of file size, a shorter transfer to the cloud for analysis and less use of power in the process, but also results in errors introduced on top of the measured signal on the pixel intensity values in the camera. Characterizing the effect the compression step has on the camera pixels therefore serves as a proxy for assessing the suitability of the compression method for numerical analysis on the of the multi – spectral data, in order to determine the optimal conditions for doing so.

In this paper, we examine different implementations of cloud-based processing for multi-spectral imaging data. Using images of a white reflectance standard and a tissue target (salami), we compare the stability of the signal over an area of a white reflectance standard, and the root mean square (RMS) error of the target tissue reflectance relative to a white light spectrometer. Four different compression methods are compared. Our results shows that mp4 movie files format is an adequate compression method for such analysis, following parsing during post-processing.

2. METHODS

2.A. Hardware and image capture

The multi-spectral imaging setup used to capture images of the cervix for analysis was described earlier^{7,8}. Briefly, a 3D printed case was designed to fit around the form factor of a smartphone case (Nexus 6). The case contained an array of 10 LEDs were mounted on a printed circuit board to illuminate the cervix, and a telescopic lens used in MobileODT's EVA System. The LEDs all had a spectral width (full width at half maximum) of ~ 20 nm; the specific wavelengths were: 420, 453, 477, 500, 520, 607, 638, 671, and 740 nm. Multi-spectral images were captured as a video using the CervDx app that controlled the smartphone camera and the LEDs. During image capture, the LEDs turned on and off sequentially; the entire process lasted under 5 seconds. Unless otherwise stated, the videos were recorded in *.mp4 format and uploaded to MobileODT's cloud server for follow on analysis. To capture data in raw format, the app Manual Camera was used instead. Videos were parsed into individual frames using Python (Version 2.7.11). An example set of multi-spectral video frames is shown in Fig. 2. The videos of the cervix were captured as part of a colposcopy procedure in a gynecology clinic in San Diego California.

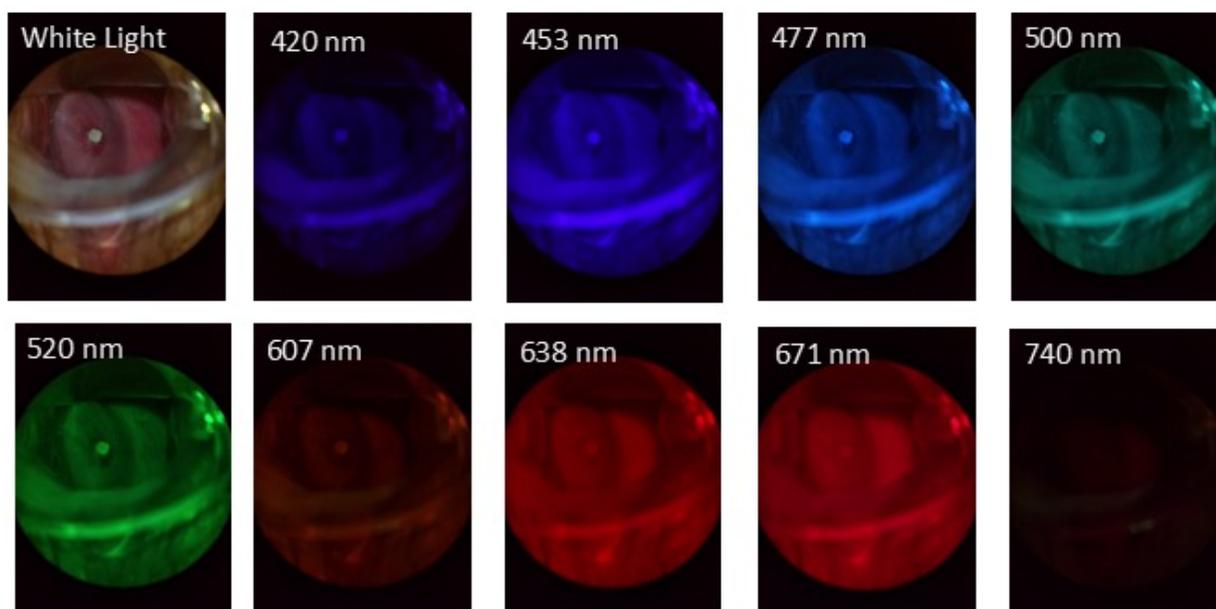


Fig. 2: Representative sample of 10 images of a cervix from a multi-spectral data set.

2.B. Comparison of compression methods

To compare different image compression methods three file formats are compared: raw *.dng images (processed both with default and non-default settings), *.jpg, and *.mp4. A video captured using MobileODT's CervDx app, with total size of 8.1MB, truncated to separate JPEG images (total size of 9.1 MB). A second set of the same scene was imaged using the Manual Camera app where image settings were set manually. A set of compressed JPEG images (total size of 9.8 MB) and a set of raw dng files (total size 250MB) were created, the Raw RGB files were converted to Grayscale using rawpi (version 0.8.0) package in two different settings, default and with set parameters of Gamma (power=2.222,slope=4.5) auto bright and Auto White Balance. Dark images were assigned as images of the same scene where all ambient light is off.

The scene imaged contained 2 regions that were analyzed – a piece of salami, and 99% Spectralon (Lab Sphere) reflectance standard (Fig. 3A). Corresponding spectral images are shown in Fig. 3B. The 2 regions of interest (ROIs) of equal size were then selected in all images covering both the reflectance standard and salami, as the video had a lower resolution the size of the ROIs was changes accordingly. Means and standard deviations were calculated.

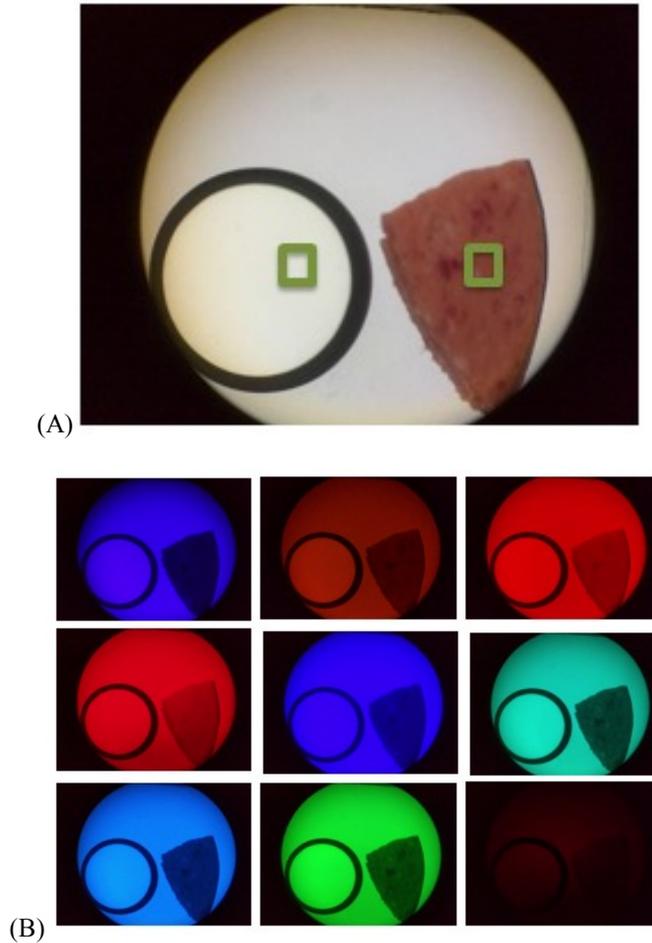


Fig. 3: (A) White light image of 99% reflectance standard (top) and salami sample (bottom). (B) Spectral images of the scene in (A).

2.C. Spectrometer measurements

As a comparison, the Spectralon and salami samples were also characterized using a spectrometer (Ocean Optics, FLAME 2000 model). The samples were illuminated using a Tungsten white light source (Ocean Optics).

2.D. Computational analyses

Differences of the mean value in the ROI of the reflectance was calculated, a sum of the distances of those values from the spectrometer measurements is denoted as the root mean square (RMS) error. Measured reflectance was calculated as the ratio of mean of the salami ROI and that of the 99% reflectance standard ROI. To evaluate the result stability the 99% reflectance ROI mean (normalized by the dynamic range) and standard deviation (STD).

3. RESULTS AND DISCUSSION

Fig. 4 compares the salami reflectance under 4 conditions – raw with default settings, raw without default settings, jpg, and parsed mp4. The measured reflectance of the salami using the multi-spectral setup, calculated as the ratio of the mean salami ROI value to the mean spectralon ROI value, is marked as circles. Variation in the white standard ROI is shown as X's, with vertical error bars representing the ratio of the standard deviation to the mean. The entire spectrum is shown in the solid curve.

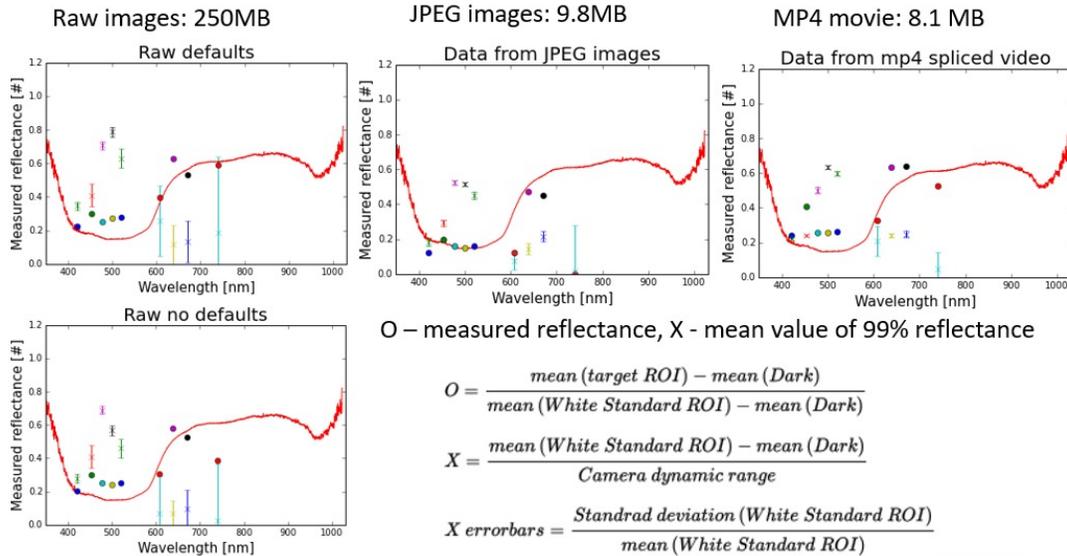


Fig. 4: Comparison of salami reflectance analyzed under 4 compression methods – raw with default settings (top left), raw without default settings (bottom left), jpg (top center), and parsed mp4 files (top right).

Fig. 5 shows a more reduced representation of the data, looking at the RMS error of the salami images relative to the spectrometer, and the standard deviation of the white standard. The smallest variation in the reflectance standard was found in the parsed mp4 files. Also, it can be seen the raw files with default settings has the smallest error relative to the spectrometer at 0.017, with parsed mp4 files at 0.080. The other compression methods (jpg and raw without default settings) had an RMS error above 0.2.

Together, these results suggest that the parsed mp4 file compression method is a good compromise, since it gives the most stable results with low RMS error. This was surprising, since the (closed) mp4 compression algorithm in the (closed) camera image capture method behaves as a “black box inside of a black box”.

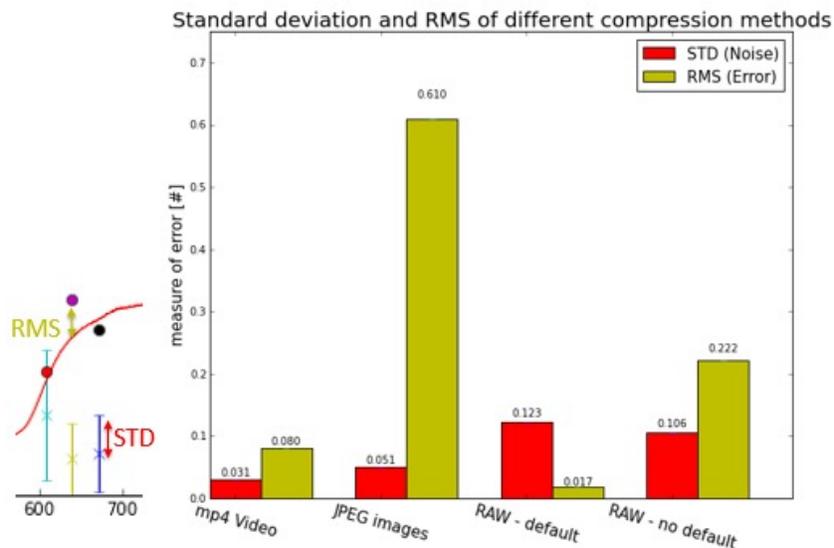


Fig. 5: Standard deviation and RMS error for different compression methods – raw with default settings, raw without default settings, jpg, and parsed mp4 files.

4. CONCLUSION

In conclusion, we found that the use of mp4 file format performs well as a compression format for data transfer to the cloud efficiently for numerical processing where the video file is more than 25 times smaller than the raw images with little compromise to the image correctness and moderate noise levels. This was determined through analyses comparing the stability of the signal from a white reflectance standard, and by comparing the calibrated reflectance signal from a salami to data from a white light spectrometer. That being said, we should also point out to the importance of setting the camera and post processing parameters in such a way that it will continue to truthfully represent the images scene.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. Bruce Kahn of Scripps clinic for capturing the data in Fig. 2, and Steve Jacques of Oregon Health & Science University for insightful conversations.

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