Energy Consumption Analysis of Image Encoding and Decoding Algorithms

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***Abstract*—*Context:* energy consumption represents an important issue with limited and embedded devices. Such devices, e.g. smartphones, process many images, both to render the UI and for application specific purposes.**

***Goal:* we aim to evaluate the energy consumption of different image encoding/decoding algorithms.**

***Method:* we run a series of experiments on a ARM based platform and we collected the energy consumed in performing typical image encoding and decoding tasks.**

***Result:* we found that there is a significant difference among codecs in terms of energy consumption. Most of the energy consumption relates to the computational efficiency of the algorithm (i.e. the time performance) though the type of processing and the algorithm may affect the average power usage up to 37%, thus indirectly affecting the energy consumption.**

***Conclusion:* JPEG compression is significantly more energy efficient than PNG both for encoding and decoding. Further studies should focus on the additional features that affect energy consumption beyond computational complexity.**

I. Introduction

Technological innovations have reduced the energy and material intensity of most products. Most people have only a vague idea of how much energy they are using for different purposes, and what sort of difference they could make by changing day-to-day behavior, or investing in efficiency measures. The concept of energy-awareness is based upon a complete knowledge on how and where energy is consumed on a device.

Optimizing energy consumption is one of the most fundamental factors for an efficient battery-powered system. Research on energy consumption falls into Hardware, or Software optimization. Research that belongs to the hardware, attempts to optimize the energy consumption by investigating hardware usage through innovating new hardware devices and techniques [1]. While on the software category, research attempts to understand how the different methods and techniques of software affect energy consumption. Therefore, the software must be able to adapt itself to meet the user requirements while conserving maximum energy. From a software engineering point of view, most contributions are devoted in developing frameworks and tools for energy metering and profiling.

Multimedia data, including audio, images and video is typically resource intensive and computationally complex. For most typical applications, the system architecture exhibits severe resource constraints [2]. Some of these constraints are a limited energy supply, low CPU speed, and limited memory for data storage. These constraints provide many challenges to provide desired application capabilities.

In embedded system, for example, Raspberry Pi or Arduino multimedia processing is a great challenge. Many research studies on providing an energy-efficient multimedia platform have been reported over the years. The basic idea of these energy-efficient multimedia applications is to design and develop new methods that provide optimal performance under constrained resources. We focus on the study of analyzing energy consumption for image encoding and decoding without external devices.

Additionally, our Research is very much relevant as for mobile devices, battery capacity and energy use directly affect usability. Since battery capacity is limited and improving slowly, device architects have concentrated on extracting greater energy efficiency from the underlying components, such as the processor, the display, and the wireless subsystems in isolation [3], [4], and [5]. Unfortunately, there has been no focus on energy consumption related with image encoding and decoding process, which this research try to focus.

The remainder of this paper is structured as follows: Section II introduces the related work, Section III describes the context of our work, including instrumentation and research questions, Section IV presents results while Section V discusses them and, finally, Section VI provides conclusions and future works.

II. Related Work

Due to the orientation towards resource constraints embedded systems, significant amount of research is conducted in the area of energy efficient computing. Recent research effort has been spent on optimizing hardware related energy consumption [1]. However, less importance has been given towards energy efficient usage of hardware components by optimizing the software [6]. In [7], authors presented an approach for energy saving software by choosing the appropriate sorting algorithms. Based on experimental results, authors introduce trend functions for each implementation of the examined sorting algorithms. These trend functions are then used to decide on which algorithm to use under certain conditions or based on the users needs (faster speed vs. saving energy).

Research in this category can be further classified according to the main factors affecting energy consumption: networking, communication, application nature, memory management, and algorithms. Concerning application nature [7] image processing capabilities in resource constraints platform is becoming increasingly important. The first major group of energy efficient techniques in this area is compression.

Energy-aware data compression has previously been examined by Barr and Asanovic in [8], and by Sadler and Martonosi in [9]. Both papers investigate the effectiveness of various lossless data compression algorithms such as LZO and bzip2 on constrained embedded platforms. The results demonstrate significant energy benefits when transmitting/receiving compressed data over uncompressed data, primarily due to the higher energy costs associated with communication versus computation. In [10], authors have studied the problem of energy-efficient image transmission in a multihop wireless sensor network using JPEG2000 compression on a StrongARM SA-1000 processor. For a given image quality requirement and transmission distance, an algorithm for finding the best set of JPEG2000 compression parameters is described. Results indicate that large fractions of the total energy are spent on computation due to the high complexity of JPEG2000.

In comparison to lossless data compression, lossy image compression involves a wider range of tradeoffs because the quality of the image is related to the energy consumed during compression and transmission. In [11], authors direct attention to the issue of mapping JPEG onto resource limited processors using a design environment that makes specific use of native word lengths of the target processor. Authors designed a framework that analytically determines the optimum integer and fractional bit-widths for the signal paths in the compression process and is able to guarantee a specified precision. They used this framework to automatically generate platform targeted JPEG codec and perform experiments using the Atmel ATmega128, TI MSP430, TI TMS320C64x, and Analog Devices Blackfin ADSP-BF533 processors to measure the energy savings resulting from the precision optimization process. It shows the general result that compression/transmission is typically more energy efficient than transmission without compression is expected, but are not aware of any result of specific quantitative aspects tradeoffs in terms of processor resources and overall energy consumption.

Though much work has gone into these fields individually, there has been little work that combines these areas to analyze the system-level effects of image compression for mobile and embedded devices. Recently in [2], authors evaluated in their survey some compression algorithms from the perspective of suitability use of energy-constrained multimedia communication systems. This survey, only provide a picture of state-of-the-art energy efficient techniques that have been proposed in wireless multimedia communication but it miss the experimental study regarding energy consumption using varies image codecs for resource-constrained systems.

In our study, we performed experiments aimed at assessing image encoding and decoding energy impact in resource constraints systems.

TABLE I
THE GQM MODEL FOR OUR EXPERIMENT

Goal	*Analyze* *for the purpose* *with respect to*	different algorithms on a Raspberry Pi of assessing differences energy consumption
RQ 1	Does different codec consume different amount of energy for encoding/decoding images?	
Metric	E_i Energy consumed by the scenario i; $i \in [1, 4]$,	
RQ 2	Are energy consumption and computational performance correlated?	
Metric	E_i vs t_i Energy consumed by the scenario i; P_i vs t_i taken by the scenario i; $i \in [1, 4]$	

III. EXPERIMENT DESIGN

The aim of our research is to compare the impact of different encoding/decoding algorithms on energy consumption of a ARM-based device: a Raspberry Pi. For this purpose we performed an experiment, which measures the energy consumed to encode/decode three different raw images in PNG and JPEG formats.

A. Goal Description and Research Questions

We define our goal through the Goal-Question-Metric (GQM) approach [12]. This approach, applied to our experiment, leads to the definition of the model presented in Table I.

B. Variable selection

For this experiment we selected four independent variables, or factors:

- **Process**: the type of image processing, $\in \{\text{Decode}, \text{Encode}\}$
- **Codec**: the specific codec / algorithm used to process the image , $\in \{\text{png}, \text{jpg}\}$
- **Quality**: the quality settings used for the image processing, $\in \{\text{Q80}, \text{Q40}, \text{Q10}, \text{LL}\}$, where the former three settings are used by the *jpg* codec only, and the latter is used by the *png* codec only.
- **Image**: the input image used in the processing task, that we coded as uppercase letter from A to C.

For each codec, quality setting, and picture we run 30 times a task, which runs five times the encoding or the decoding of the same image. During each task we collected a set of measure (dependent variables) that consist of the Energy consumed (E), the average power used (P) and the time taken by the algorithm to compete each task (t). The scenarios that we observed are:

S1 (C_{Q80}) JPEG codec: in this scenario we encode/decode the input image by using the JPEG codec with Q (quality parameter) set to 80. This represents the lowest level of quality for JPEG pictures in our experiment.

S2 (C_{Q40}) JPEG codec: in this scenario we encode/decode the input image by using the JPEG codec with Q set to 40.

TABLE II
TEST IMAGES.

Image	id	width	height	file size
Baboon	A	512	512	786178 B
Scenario	B	1024	768	2179170 B
Pepper	C	1024	1024	3175172 B

This represents a medium level of quality for JPEG pictures in our experiment.

S3 (C_{Q10}) JPEG codec: in this scenario we encode/decode the input image by using the JPEG codec with Q set to 10. This represents the highest level of quality for JPEG pictures in our experiment.

S4 (C_{LL}) PNG codec: in this scenario we encode/decode the input image by using the PNG codec. PNG is a lossless image format.

We observe that the *Codec* factor brings no additional information w.r.t. the quality settings, therefore it will not be used for analysis purposes but reported only for clarity reasons.

C. Hypotheses Formulation

We can formalize our Research Question into hypotheses based on our GQM Model. For the RQ1, concerning the energy consumption of different codecs, we formulate the null hypothesis:

He_0 the factor have no significant effect on the energy used for the image processing task.

Concerning RQ2, it focuses on the relationship between energy consumption and computational performance. In particular we investigate the correlation between energy and time and between power and the other factors, we formulate the following hypotheses:

Ht_0 there is a null correlation between time and energy consumed to perform the image processing.

Hc_0 the factors (i.e. Image, Process, Quality) have no significant effect on the power used during the image processing tasks.

D. Instrumentation and Experiment Design

The selected usage scenarios have been implemented in C++ code and compiled with g++. In order to obtain a statistically relevant data set, we created a task composed of five repetition of the same encoding/decoding, and each task has been repeated 30 times.

In our experiment we used three different benchmark images whose characteristics are reported in Table II. It shows information in term of dimensions in pixels and size of the uncompressed BMP file that we used as input for the image encoding process.

1) Hardware Instrumentation: The experiment has been performed on a Raspberry Pi running the Raspbian Linux distribution.

The energy consumption data was acquired through a power meter *called USB Tester OLED Backpack 2.0* [1]. This device gets current and voltage with a sampling frequency of 10 Hz, and it is placed between the power source and the Raspberry Pi. The power meter also has a dedicated output port, detected as a keyboard, which sends the collected data to another device (in our case a Laptop).

2) Software Setup: Working on a Linux environment we created a script, which automatizes the execution of the different scenarios. We separate one single execution from another with a sleep and a while(1) loop, which last a predefined amount of time. By doing this we can read the energy data and understand from which part of the script it has been collected because the sleep has the lowest energy consumption value, while the while(1) loop has the highest energy consumption value.

The presence of the sleep slots allow us to estimate the idle power consumption and subract it from the task power to obtain the additionl power induced by the image processing alone.

E. Analysis Methodology

Concerning the first hypothesis (He_0) we will perform an ANOVA analysis to identify the factors that directly or through interaction affect the energy consumption. The model used for the ANOVA will include both the simple terms corresponding to the factors $Process$, $Quality$ and $Image$ and their first and second order interaction terms.

Concerning the other two hypotheses, in practice we will check the correlation between the energy and the time, which correspond to the equivalence:

$$E = P \cdot t$$

In addition, will investigate the effects of the independent factors on the average power consumption of the image processing tasks. For this purpose we fit a linear model with the following (simplified) form:

$$\begin{aligned} P = \quad & c_0 + c_{Encode} \cdot i_{Encode} + \\ & c_{Q40} \cdot i_{Q40} + c_{Q10} \cdot i_{Q10} + c_{LL} \cdot i_{LL} + \\ & c_B \cdot i_B + c_C \cdot i_C \end{aligned} \tag{1}$$

where c_{Level} is a coefficient for the $Level$ term, and i_{Level} is an indicator variable for the factor F with value:

$$i_{Level} = \begin{cases} 0 & \text{if} \quad F \neq Level \\ 1 & \text{if} \quad F = Level \end{cases}$$

The model we will fit, will include not only the simple terms shown in equation (1) but also the first and second order interactions, as for the ANOVA model.

In order to apply the ANOVA and linear model fitting we should check mainly for the normality of the data, which we will do by means of the Shapiro-Wilk test. If the test return a a

[1]https://friedcircuits.us/docs/usb-tester-oled-backpack-2-0/ Last Visited 26 January 2015

p-value smaller than a given α level it is possible to conclude that the data is not drawn from a normal distribution.

In general we will draw conclusions from our tests based on a significance level $\alpha = 0.05$, i.e. we accept a 5% risk of type I error – rejecting the null hypothesis when it is actually true –.

F. Threats to validity

We can identify a few different threats, which could affect the validity of our experimental results. They are classified according to [13].

Internal validity: the first threat is related to the sampling frequency of the power meter we used to collect energy consumption data. The selected sampling frequency (10 Hz) has the advantage to produce a controlled amount of data but, on the other hand, it may result into a limited granularity and miss some finer phenomena. To overcome this problem we run many times the same operation in order to lengthen the execution of the single task and collect more data.

Construct validity: the second threat is characterized by the energy consumption due to the operating system (I/O, process scheduling, etc.), which may confound the measurement of the energy consumed by the encoding and decoding operations – our main construct –. This consumption is an almost constant offset that is spread for all the measurements, in addition we compute the energy consumed in each task by subtracting the "background" power attributable to the OS from the measured power, therefore the result can be considered as the energy consumption due to the sole image processing task.

Conclusion validity: we checked our data and applied the appropriate statistical tests using a standard significance level.

External validity: finally, the absolute values of energy and power consumption are specific to a specific single device, though they are representatives of a very popular category of devices with similar specifications[2].

We expect to find similar trends and ratios in devices, e.g. mobile phones, which use similar ARM-based processor architectures.

IV. Results

For the purpose of replication and peer scrutiny we made available a replication package containing the raw data and the images used in the processing tasks[3].

A. Summary statistics

First of all we report the summary descriptive statistics of the energy consumed by the different processes, codecs, and relative quality settings, in Table III. The table also reports the time employed to perform the image processing task.

We observe that, on average, PNG decoding requires roughly two times as much energy as the highest quality JPEG (Q10), to achieve visually similar results. The difference is even more stark when encoding is concerned: the energy required by PNG is six times higher than JPEG. The detailed distribution of the values can be observed by means of the boxplots reported in Figure 1.

TABLE III
Summary statistics.

Process	Codec	Quality	Energy [J] mean	Energy [J] sd	Time [s] mean	Time [s] sd
Decode	jpg	Q80	0.68	0.30	2.9	1.2
	jpg	Q40	0.76	0.33	3.4	1.4
	jpg	Q10	0.94	0.37	4.5	1.6
	png	LL	1.78	0.80	9.6	4.3
Encode	jpg	Q80	0.78	0.36	5.9	2.7
	jpg	Q40	0.84	0.37	6.1	2.7
	jpg	Q10	1.05	0.41	7.6	3.0
	png	LL	6.16	2.98	36.0	18.0

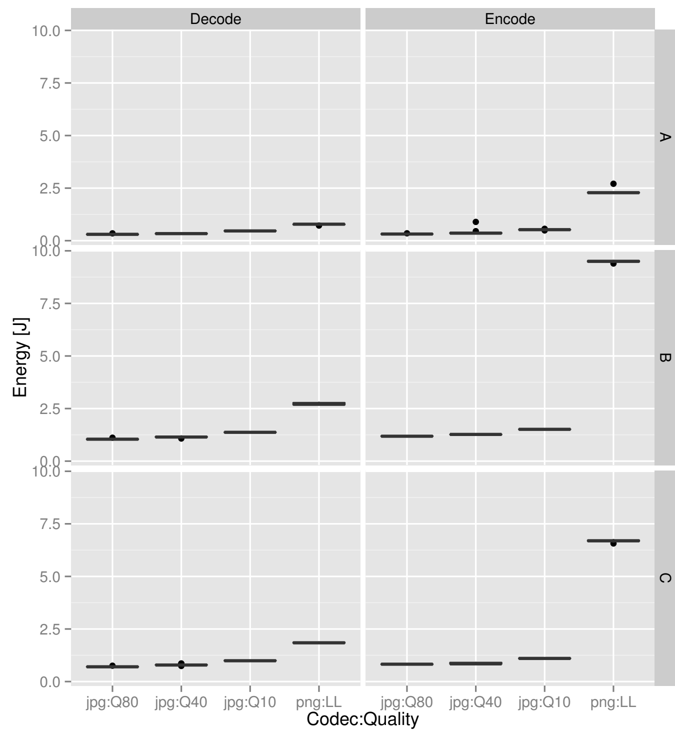

Fig. 1. Energy consumption by process, codec, and quality setting

We can observe from the boxplots that the Energy values have very small dispersion, once process type, quality, and image are controlled. The standard deviation reported in III is relatively larger because it includes the three different images, which require notably different energy to process.

We checked for the normality of the Energy values in each group using the Shapiro-Wilk test. We found evidence of non normality in no group. This result allow us to use the normal parametric statistical tests.

[2]http://goo.gl/Zfltcx Last Visited 26 January 2015
[3]http://softeng.polito.it/torchiano/GREENS2015_exp_package.zip

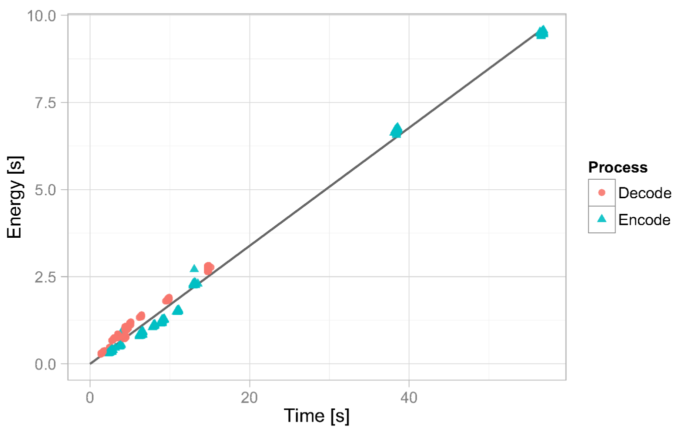

Fig. 2. Energy vs. Time.

We can observe in Figure 1 a difference between encoding and decoding process, this difference is confirmed by means of a Mann-Whitney test (p=<**0.001**).

B. RQ1: Energy consumption of codecs

To analyze the dependence of the Energy consumption on the factors of our experiment we conducted a three-way ANOVA of *Energy* vs. *Process type*, *Quality*, and *Image*. We decided not to include the codec explicitly because the quality setting subsumes the information about the codec used. The analysis include simple terms plus first and second order interaction terms, the results are reported in Table IV.

We can observe that all predictors in the analysis of variance are highly significant. The relative strength of the influence on the Energy can be understood by looking at the sum of squares (*Sum Sq* column). The quality of the image processing has the highest influence, explaining 43% of the variation, then we have the interaction term of Process and Quality (29% of variation) and the specific Image that is processed (13%). The percentage of variance that remain unexplained is 0.03%, a value that is perfectly compatible with the measurement error.

Based on these results we can reject the null hypothesis He_0.

C. RQ2: Energy and computational efficiency

In this context we consider only time efficiency. Therefore we study the correlation between the time required to perform the processing and the energy consumed.

Figure 2 reports the scatter plot of the *Energy* vs. *time*.

The simple correlation between *time* and *Energy* is very high (R^2=98.97%), the corresponding regression line is reported in light gray in the figure together with the data points collected in our experiment. In practice the duration of the processing alone (either encoding or decoding) is able predict well enough most of the energy consumption.

Based on this we can reject the null hypothesis Ht_0.

This is quite reasonable and confirms what we knew from the definition of energy:

$$Energy = time \cdot Power$$

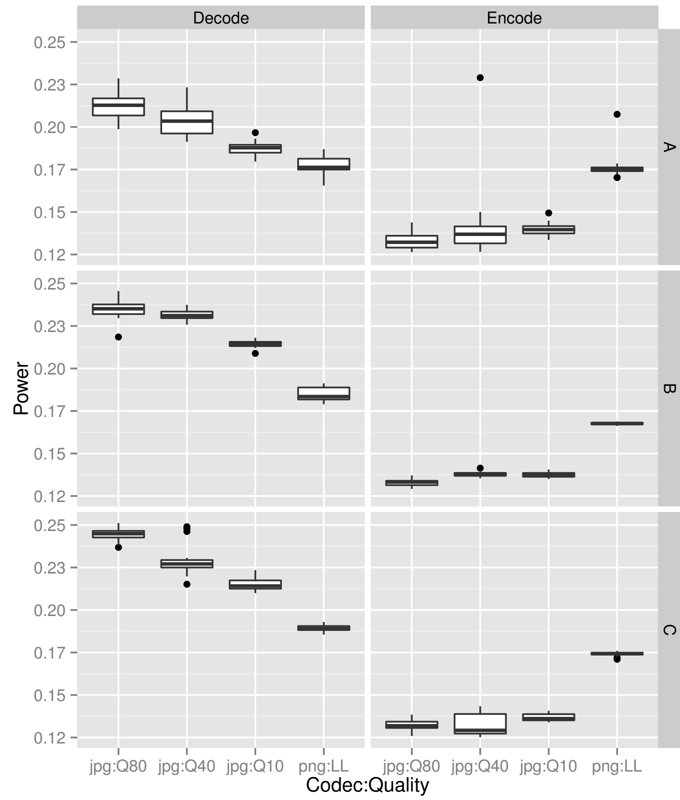

Fig. 3. Power consumption for different Process, Codec, Quality and Image.

What we aim to understand is which factors influence the *Power* term and what is the relative magnitude of their effect. The values of *Power* for the different factor combinations are shown as boxplots in Figure 3. They represent the average power during each processing task.

To understand which factors influence the power we performed a linear model regression fitting of *Power* versus *Process type*, *Quality*, and *Image* including the second and third order interaction terms.

The coefficients are reported in Table V. We observe that most coefficients are statistical significant, the exception being the interaction terms $c_{Q10:C}$, $c_{Encode:Q40:C}$, and $c_{Encode:Q10:C}$. In particular all the coefficients of the simple effects of Process, Quality and Image are statistically significant. Based on this result we reject the null hypothesis Hc_0.

V. Discussion

A. RQ1: Energy consumption of codecs

Our result confirm a significant difference in terms of Energy consumption that depends heavily on the codec and quality settings used (RQ1).

A more practical quantification can be appreciated in Table VI, which reports the normalized energy, fixing the energy for the JPEG process with quality Q10 at the conventional value 100. Decoding a PNG (LossLess) image may require 66% to 99% more energy than the highest quality JPEG. The difference is even more noticeable when looking at the

TABLE IV
ANOVA OF ENERGY VS. PROCESS, QUALITY AND IMAGE

Term	Df	Sum Sq	Mean Sq	F value	Pr(>F)	SSq %
Process	1	243.7	243.7	177060	<**0.001**	7.83%
Quality	3	1330	443.3	322081	<**0.001**	42.73%
Image	2	390.1	195.1	141707	<**0.001**	12.53%
Process:Quality	3	621.3	207.1	150463	<**0.001**	19.96%
Process:Image	2	58.87	29.43	21384	<**0.001**	1.89%
Quality:Image	6	314.5	52.41	38078	<**0.001**	10.1%
Process:Quality:Image	6	152.9	25.48	18514	<**0.001**	4.91%
Residuals	696	0.958	0.001376			0.03%

TABLE V
COFFICIENT MODEL POWER VS. PROCESS, QUALITY AND IMAGE

	Estimate	Std..Error	t.value	Pr...t..
(Intercept) c_0	0.2126	0.0010	202.51	<**0.001**
c_{Encode}	-0.0796	0.0015	-53.60	<**0.001**
c_{Q40}	-0.0090	0.0015	-6.04	<**0.001**
c_{Q10}	-0.0256	0.0015	-17.23	<**0.001**
c_{LL}	-0.0360	0.0015	-24.27	<**0.001**
c_{B}	0.0223	0.0015	15.00	<**0.001**
c_{C}	0.0316	0.0015	21.32	<**0.001**
$c_{Encode:Q40}$	0.0153	0.0021	7.28	<**0.001**
$c_{Encode:Q10}$	0.0323	0.0021	15.37	<**0.001**
$c_{Encode:LL}$	0.0790	0.0021	37.61	<**0.001**
$c_{Encode:B}$	-0.0223	0.0021	-10.63	<**0.001**
$c_{Encode:C}$	-0.0326	0.0021	-15.50	<**0.001**
$c_{Q40:B}$	0.0056	0.0021	2.67	**0.0078**
$c_{Q10:B}$	0.0052	0.0021	2.46	**0.0142**
$c_{LL:B}$	-0.0141	0.0021	-6.74	<**0.001**
$c_{Q40:C}$	-0.0071	0.0021	-3.38	<**0.001**
$c_{Q10:C}$	-0.0037	0.0021	-1.76	0.0786
$c_{LL:C}$	-0.0189	0.0021	-9.01	<**0.001**
$c_{Encode:Q40:B}$	-0.0070	0.0030	-2.37	**0.0180**
$c_{Encode:Q10:B}$	-0.0073	0.0030	-2.45	**0.0146**
$c_{Encode:LL:B}$	0.0058	0.0030	1.97	**0.0496**
$c_{Encode:Q40:C}$	0.0013	0.0030	0.43	0.665
$c_{Encode:Q10:C}$	0.0016	0.0030	0.54	0.587
$c_{Encode:LL:C}$	0.0181	0.0030	6.09	<**0.001**

encoding where we can observe up to a 6 times increase in energy.

TABLE VI
NORMALIZED ENERGY PER IMAGE AND PROCESSING.

Process	Image	jpg:Q80	jpg:Q40	jpg:Q10	png:LL
	A	65	73	100	166
Decode	B	76	84	100	199
	C	71	80	100	185
	A	61	73	100	439
Encode	B	79	84	100	628
	C	75	79	100	608

B. RQ2: Energy and computational efficiency

As expected we observe a strong correlation between Energy and time (RQ2)

In addition we identified an significant influence of the experimental factors on the power consumption of the image processing tasks. In particular the type of processing (encoding or decoding) plays an important role. Also the type of codec is highly relevant (RQ2).

Observing the regression of Power vs. the experimental factors (see table V), the intercept c_0 represent the average power of the decoding task of image A using the JPEG algorithm with the Q80 quality setting.

We can compare the individual coefficients to the Intercept to asses their relative importance. In particular we notice that the factor with the highest influence corresponds to the coefficient c_{Encode} that affects the average power by 37.43%, i.e. we can expect an average corresponding increase of the power when we perform a Encode process (vs. Decode). More in general we have 9 coefficients that correspond to an effect larger than 10% of the intercept.

When comparing the two boxplots in Figure 1 and Figure 3 we can notice that the differences by Codec, Quality and Process type are much more limited and that overall the Power for decoding is higher than the one for encoding, while considering the Energy we have the opposite. This is confirmed by the regression coefficient c_{Encode} that has a negative value. In practice the encoding average power is 80 mW (37%) higher, though the duration is much shorter – 2 to 4 times (see table III) – and therefore the overall energy consumed is smaller.

More in details, the two boxplots reveal how, e.g. for the decoding process, the lossless PNG algorithm (LL) exhibits a lower average power consumption than the JPEG algorithm at any quantization level. Nevertheless it consumes more energy because, to encode the same image it takes more time.

The above considerations tell us that the relationship between Energy and algorithm is complex: it involves heavily the computational performance (i.e. the time required to complete the task) but different algorithms draw significantly different levels of power.

VI. Conclusions and Future Works

We conducted an experiment to assess the energy and power consumption of image processing (encoding and decoding) algorithms.

Our results identify *JPEG* as the most energy efficient algorithm both for encoding and decoding images. From the perspective of portable devices, as far as image rendering is concerned, using PNG instead of a high-quality JPEG image may increase energy consumption up to 66% or conversely reduce battery duration by 40%.

Concerning the relationship between the computational efficiency and the energy consumption, we observe a strong influence of complexity on the energy, though the different level of power usage between codecs open interesting possibilities concerning power-related optimizations. Our further work will focus on investigating such aspects. In addition we would like to investigate other aspects – e.g. space complexity – that we did not address in this study.

References

[1] A. Bardine, P. Foglia, G. Gabrielli, and C. A. Prete, "Analysis of static and dynamic energy consumption in nuca caches: initial results," in *Proceedings of the 2007 workshop on MEmory performance: DEaling with Applications, systems and architecture*. ACM, 2007, pp. 105–112.

[2] T. Ma, M. Hempel, D. Peng, and H. Sharif, "A survey of energy-efficient compression and communication techniques for multimedia in resource constrained systems," *Communications Surveys & Tutorials, IEEE*, vol. 15, no. 3, pp. 963–972, 2013.

[3] C. E. Jones, K. M. Sivalingam, P. Agrawal, and J. C. Chen, "A survey of energy efficient network protocols for wireless networks," *Wirel. Netw.*, vol. 7, no. 4, pp. 343–358, Sep. 2001. [Online]. Available: http://dx.doi.org/10.1023/A:1016627727877

[4] P. Pillai and K. G. Shin, "Real-time dynamic voltage scaling for low-power embedded operating systems," in *Proceedings of the Eighteenth ACM Symposium on Operating Systems Principles*, ser. SOSP '01. New York, NY, USA: ACM, 2001, pp. 89–102. [Online]. Available: http://doi.acm.org/10.1145/502034.502044

[5] S. Rivoire, M. A. Shah, P. Ranganathan, and C. Kozyrakis, "Joulesort: A balanced energy-efficiency benchmark," in *Proceedings of the 2007 ACM SIGMOD International Conference on Management of Data*, ser. SIGMOD '07. New York, NY, USA: ACM, 2007, pp. 365–376. [Online]. Available: http://doi.acm.org/10.1145/1247480.1247522

[6] H. Höpfner and C. Bunse, "Towards an energy-consumption based complexity classification for resource substitution strategies." in *Grundlagen von Datenbanken*, 2010.

[7] C. Bunse, H. Höpfner, S. Roychoudhury, and E. Mansour, "Energy efficient data sorting using standard sorting algorithms," in *Software and Data Technologies*, ser. Communications in Computer and Information Science, J. Cordeiro, A. Ranchordas, and B. Shishkov, Eds. Springer Berlin Heidelberg, 2011, vol. 50, pp. 247–260. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-20116-5_19

[8] K. C. Barr and K. Asanović, "Energy-aware lossless data compression," *ACM Trans. Comput. Syst.*, vol. 24, no. 3, pp. 250–291, Aug. 2006. [Online]. Available: http://doi.acm.org/10.1145/1151690.1151692

[9] C. M. Sadler and M. Martonosi, "Data compression algorithms for energy-constrained devices in delay tolerant networks," in *Proceedings of the 4th International Conference on Embedded Networked Sensor Systems*, ser. SenSys '06. New York, NY, USA: ACM, 2006, pp. 265–278. [Online]. Available: http://doi.acm.org/10.1145/1182807.1182834

[10] H. Wu and A. Abouzeid, "Power aware image transmission in energy constrained wireless networks," in *Computers and Communications, 2004. Proceedings. ISCC 2004. Ninth International Symposium on*, vol. 1, June 2004, pp. 202–207 Vol.1.

[11] D.-U. Lee, H. Kim, M. Rahimi, D. Estrin, and J. D. Villasenor, "Energy-efficient image compression for resource-constrained platforms," *Image Processing, IEEE Transactions on*, vol. 18, no. 9, pp. 2100–2113, 2009.

[12] R. Van Solingen and E. Berghout, *Goal/Question/Metric Method*. McGraw-Hill Inc.,US, January 1999.

[13] C. Wohlin, P. Runeson, M. Höst, M. C. Ohlsson, B. Regnell, and A. Wesslén, *Experimentation in software engineering*. Springer Science & Business Media, 2012.