On Effectiveness of Lossless Compression in Transferring mHealth Data Files

Armen Dzhagaryan, Aleksandar Milenkovic
Electrical and Computer Engineering Department
The University of Alabama in Huntsville
Huntsville, AL

***Abstract*—The health and fitness data traffic originating on mobile devices has been continually increasing, with an exponential increase in the number of personal wearable devices and mobile health monitoring applications. Lossless data compression can increase throughput, reduce latency, and achieve energy-efficient communication between personal devices and the cloud. This paper experimentally explores the effectiveness of common compression utilities on mobile devices when uploading and downloading a representative mHealth data set. Based on the results of our study, we develop recommendations for effective data transfers that can assist mHealth application developers.**

Keywords—mobile sensing; health monitoring; wearable devices; data communication.

I. INTRODUCTION

Recent technology advances in wearable devices, mobile computing, wireless communication, and cloud computing have enabled the proliferation of mobile health and fitness monitoring systems (mHealth systems for short). These systems spurred a number of smart applications for fitness monitoring, health monitoring, exercise guidance, sports training, rehabilitation and testing in ambulatory conditions [1], [2].

mHealth systems typically include one or more wearable devices, strategically placed on the human body to capture and transfer vital signs and activity data to an mHealth application running on a personal device [3]. A number of new wearable devices suitable for mHealth have been introduced recently in the form of smart socks, wrist bands, smartwatches, chest belts or smart shirts. They typically track the level of physical activity and body posture by analyzing signals from inertial sensors, such as accelerometers, gyroscopes, and magnetic sensors. In addition, they track vital signs by analyzing data from physiological sensors such as ECG, EEG, breathing sensor, and blood pressure cuffs. The processed data are sent to personal mHealth applications running on a personal device, typically a smartphone or a tablet. The personal devices include more processing power and storage capacity and may provide real-time feedback and guidance to the user. To ensure long-term storing and analysis of fitness and health status over extended periods of time, the personal devices upload the mHealth data to the cloud. In addition, the user can retrieve his or her previously recorded mHealth data anytime from the cloud.

With a continual growth of the number and type of wearable devices and their market proliferation, the amount of data that needs to be transferred between personal devices and the cloud is growing exponentially. These data transfers take time, network bandwidth, and energy resources. Long latencies and short battery life may have a negative impact on user experience. One way to lower communication latencies, improve battery life, and make more effective use of available bandwidth and storage is to use data compression. Compressing data on the personal mobile device before uploading them to the cloud reduces the number of bytes that needs to be transferred. Similarly, when downloading data from the cloud, compressed files are shorter and take less time to transfer than uncompressed files. However, additional latency and energy for performing compression/decompression on the personal device may outweigh the benefits due to shorter transfer times. Thus, it is important to explore the design space and develop recommendations for effective data transfers in the context of mobile health monitoring applications.

This paper explores effectiveness of common compression utilities *gzip*, *lzop*, *bzip2*, and *xz* in transferring mHealth data between a personal device and the cloud. Specifically, we want to determine (a) whether compression reduces the latency and energy consumption of mHealth data transfers, and (b) which compression utilities result in the best performance and energy efficiency. The effectiveness of compression in transferring mHealth data depends on many factors, including the type of mHealth data, data encoding, file size, network bandwidth, type of compression utility, and performance of personal devices. To thoroughly explore the design space, we compile a data set with different types of mHealth data, representing typical mHealth applications (Section II). Using our experimental setup (Section III), we examine several performance metrics, including the compression ratio, the effective upload and download throughputs over a wireless interface, as well as the energy efficiency. The results (Section IV) indicate that compressed uploads and downloads can indeed reduce latency and save energy when transferring some types of mHealth data. Based on the results of our experimental study, we develop a set of recommendations for effective data transfers that can help inform developers of future mHealth applications.

This work was supported in part by the U.S. National Science Foundation under grant CNS-1205439 and CNS-1217470.

II. DATA SETS

To evaluate effectiveness of compression and decompression in the context of mobile health monitoring applications, we need a set of representative data. Although repositories such as PhysioNet [4], [5] include a diverse set of physiological data, these data are recorded in professional medical setups and as such are not quite representative of mobile wearable systems. Consequently, we embarked upon creating a set of representative data collected on the state-of-the-art wearable monitors.

mHealth applications vary broadly in scope, the number and type of sensors required, their accuracy, sampling frequency, the length of the reporting period, and data encoding. To cover a broad range of mHealth applications, we design a data set that includes a diverse set of files with mHealth data. Table 1 describes the data set, including the sampling frequency, data encoding, and data storing. It includes binary (.dat) and text files (.csv) containing the following: (a) samples captured on an ECG sensor (ECG.WAVE), a breathing sensor (BB.WAVE), and an accelerometer (ACC.WAVE); (b) time intervals between two breaths (BB.TIME) and two R-peaks in electrocardiogram (RR.TIME), and (c) summary logs including a number of physiological parameters reported periodically. The data are recorded using a Zephyr Technologies' BioHarness 3 physiological monitor [6].

TABLE I. TYPES OF PHYSIOLOGICAL DATA FILES

Data File	Description
ECG. WAVE	Electrocardiogram waveform; 250 samples per second, 12-bit samples; stored as 16-bit unsigned integers
BB. WAVE	Breathing waveform; 25 samples per second, 24-bit samples; stored as 32-bit unsigned integers
ACC. WAVE	Acceleration waveform for the Vertical, Lateral, and Sagittal Axis; 100 samples per second per axis, 12-bit samples; stored as three 16-bit unsigned integers per sample
BB. TIME	Time distance between two consecutive breaths in milliseconds; reported for each breath detection; stored as a 16-bit unsigned number
RR. TIME	Time distance between two consecutive R-peaks in milliseconds; reported for each R-peak detection; stored as a 16-bit unsigned integer
SUM. LOG	Periodic summary log containing the average heart rate, breathing rate, posture, level of physical activity, skin temperature, min/max acceleration, ECG amplitude, ECG noise level, and battery status; reported once every second

TABLE II. ACTIVITIES OF DAILY LIVING

Activities	Description
Sleeping	415 minutes of sleeping
Daily Activities	135 minutes of various activities including driving, walking, office activities
Walking	45 minutes of walking at medium speed
7-min Workout	7 minutes of high intensity circuit training using body weight [7], a.k.a. the scientific 7-minute workout
Exercising	70 minutes of boot camp exercise routine that involves alternating aerobic intervals and athletic drills with strengthening intervals

The amount of redundancy found in the mHealth data is expected to vary with varying types of the subject's activity. For example, a stream of samples from accelerometer will have more redundancy when the user is sleeping than when the user is going through a high intensity workout. To cover different types of activities of daily living we consider several activities described in Table 2, ranging from sleeping to high-intensity exercise session. Table 3 shows the sizes of the uncompressed mHealth files for different activities in the binary and text file formats. These sizes show that mHealth applications indeed can generate a quite considerable amount of data, posing challenges to their storing, retrieval, and communicating.

TABLE III. BINARY AND TEXT FILE SIZES IN MEGABYTES

		ACC. WAVE	BR. WAVE	ECG. WAVE	B2B. TIME	R2R. TIME	SUM LOG
Sleeping	BIN	14.36	2.39	11.97	0.011	0.039	3.26
	CSV	95.75	19.75	179.53	0.039	0.127	4.69
Daily Activities	BIN	4.63	0.77	3.86	0.005	0.020	1.05
	CSV	30.88	6.37	57.90	0.019	0.060	1.52
Walking	BIN	1.60	0.27	1.34	0.003	0.008	0.36
	CSV	10.68	2.20	20.03	0.010	0.025	0.53
7-min Workout	BIN	0.39	0.07	0.33	0.001	0.003	0.09
	CSV	2.61	0.54	4.89	0.008	0.008	0.13
Exercising	BIN	2.58	0.43	2.15	0.004	0.019	0.59
	CSV	17.21	3.55	32.27	0.015	0.057	0.85

III. EXPERIMENTAL SETUP

To evaluate the effectiveness of compression utilities in transferring the mHealth data we measure file sizes (US – uncompressed file size, CS – compressed file size), execution times to perform compression (T.C) and decompression tasks (T.D), and times to upload and download uncompressed files (T.UUP and T.UDW). A useful metric for describing efficiency of networked data transfers is the effective throughput, Th, expressed in megabytes per second [8]. For uncompressed file uploads Th.UUP is determined as US/T.UUP; for compressed file uploads the effective upload throughput is Th.CUP = US/(T.UUP/CR + T.C), where CR is the compression ratio. In addition to determining the impact of compression on latency of network transfers, we use our experimental setup [9] to measure the energy consumed when uploading and downloading the mHealth files over a wireless interface (with and without compression/decompression). Instead of reporting the total energy in Joules, we report energy efficiency expressed in megabytes per Joule allowing for easy comparison of compressed and uncompressed data transfers. Table 4 summarizes the metrics used as well as their definitions.

TABLE IV. MEASURED AND DERIVED METRICS

Symbol	Description	Units	Definition
US	Uncompressed file size	MB	Measured
CS	Compressed file size	MB	Measured
T.C [T.D]	Time to [de]compress	s	Measured
T.UUP [T.UDW]	Time to upload [download] the uncompressed file	s	Measured
ET.C [ET.D]	Total energy for [de]compression	J	Measured
ET.UUP [ET.UDW]	Total energy for upload [download] of the uncompressed file	J	Measured
CR	Compression ratio	-	US/CS
Th.UUP [Th.UDW]	Uncompressed upload [download] throughput	MB/s	US/T.UUP [US/T.UDW]
Th.CUP [Th.CDW]	WLAN compressed upload [download] throughput	MB/s	US/(T.C+T.UUP/CR) [US/(T.D+T.UDW/CR)]
EE.UUP [EE.UDW]	Uncompressed upload [download] energy efficiency	MB/J	US/ET.C [US/ET.D]
EE.CUP [EE.CDW]	WLAN compressed upload [download] energy efficiency	MB/J	US/(ET.C+ET.UUP/CR) [US/(ET.D+ET.UDW/CR)]

As the personal device we use an OnePlus One smartphone running Android OS [10]. The smartphone is instrumented to support energy measurements and can run common compression/decompression utilities such as *gzip*, *lzop*, *bzip2*, and *xz*. These utilities support a number of compression levels that allow a user to trade off speed for compression ratio. Lower levels favor speed whereas higher levels result in better compression. To reduce the number of measurements we focus on default compression levels for each utility. The smartphone connects to the Internet via a wireless network interface and exchanges the data with the cloud.

The goal of our experiments is to determine whether the mHealth data files should be compressed before they are uploaded to the cloud or they should be uploaded uncompressed. Similarly, we want to determine whether the mHealth data should be downloaded as the compressed files and then decompressed on the smartphone or they should be downloaded as uncompressed files. We also want to determine which compression utilities are the most effective.

IV. Results

A. Compression Ratio

Table 5 shows the compression ratio for the mHealth binary and csv files as a function of different activities. Expectedly, the compression ratio is significantly higher for the csv files than for the binary files. *bzip2* and *xz* achieve the best compression ratios, regardless of the type of mHealth data and encoding, whereas *lzop* achieves the lowest compression ratio. The results indicate that the type of activity impacts the compression ratio. Thus, all the utilities achieve the highest compression ratio for the *Sleeping* activity and the lowest for the *Exercising* activity. For example, *gzip* compresses the binary ACC.WAVE 4.5 times for the *Sleeping* and only 2.1 times for the *Exercising* activity.

The results show that the compression ratios vary widely for different mHealth file types. Thus, the summary health logs (SUM.LOG) are highly compressible because they include a lot of redundant information (e.g., time stamps). For example, *gzip* reduces the binary SUM.LOG files between 8.5 and 4.3 times for the *Sleeping* and *Exercising* activity, respectively. The low compression ratio is observed for the R2R.TIME and especially for B2B.TIME binary files and they should be transferred uncompressed.

B. Effective WLAN Throughput and Energy Efficiency

Table 6 shows the effective throughput on the WLAN interface for the uncompressed uploads (Th.UUP) and the compressed uploads with different compression utilities. Note: in the rest of the paper, due to space limitations, we will discuss the results for only two activities, *Sleeping*, that achieves the highest compression ratios, and *Exercising* with the lowest compression ratios. The compressed uploads shorten latency only if their effective throughput exceeds the throughput of the uncompressed uploads. The following observations are derived from the results in Table 6.

- *lzop* and *gzip* improve effective throughput for the text file uploads, with *lzop* often offering the best results in spite of relatively small compression ratio.
- *lzop* improves the effective throughput for the binary file uploads for all types of mHealth data. *gzip* does not offer significant improvements when transferring binary data files, except for SUM.LOG files.
- *bzip2* and *xz* utilities do not improve effective throughput relative to the uncompressed uploads and should not be used. This recommendation holds for both the binary and text files. In spite of their superior compression ratios, the time needed to perform compression often exceeds the gains due to uploading smaller files.
- The B2B.TIME and R2R.TIME files should be uploaded uncompressed.
- The type of the activity and the size of the mHealth files impact the effective throughput.

TABLE V. COMPRESSION RATIO FOR BINARY AND CSV FILES

	ACC. WAVE		**BR. WAVE**		**ECG. WAVE**		**B2B. TIME**		**R2R. TIME**		**SUM. LOG**	
	BIN	**CSV**	**BIN**	**CSV**	**BIN**	**CSV**	**BIN**	**CSV**	**BIN**	**CSV**	**BIN**	**CSV**
	Sleeping											
gzip -6	4.5	8.9	2.5	6.7	4.1	8.2	1.3	4.1	1.6	4.2	8.5	10.6
lzop -6	2.2	4.6	1.6	4.4	2.1	5.0	1.0	2.8	1.0	2.7	4.5	5.1
bzip2 -9	6.5	14.0	3.6	9.9	7.8	11.6	1.6	5.9	2.0	6.7	13.1	17.4
xz -6	6.2	21.9	3.4	14.1	6.9	31.0	1.3	4.9	1.9	5.2	13.5	16.9
	Activities of Daily Living											
gzip -6	3.1	7.9	1.9	6.0	3.3	7.9	1.2	3.8	1.6	4.1	5.1	7.0
lzop -6	1.9	4.4	1.2	4.0	1.9	4.9	1.0	2.6	1.0	2.6	3.2	3.9
bzip2 -9	4.6	12.0	2.5	8.7	5.9	11.1	1.3	5.2	2.2	6.5	8.1	11.4
xz -6	5.0	18.9	2.4	11.6	5.0	27.2	1.2	4.2	2.0	5.3	7.9	11.1
	Walking											
gzip -6	2.2	6.3	1.9	6.0	2.8	7.3	1.3	4.1	1.8	4.7	5.1	7.0
lzop -6	1.4	3.8	1.3	3.9	1.6	4.6	1.0	2.7	1.0	2.8	3.2	3.9
bzip2 -9	3.4	9.9	2.4	8.8	5.0	10.4	1.4	5.6	2.5	7.5	8.2	11.4
xz -6	3.5	14.4	2.4	11.2	4.0	22.7	1.2	4.4	2.4	5.9	7.7	11.4
	7 min Workout											
gzip -6	2.3	6.7	1.6	5.6	2.1	7.0	1.1	3.4	1.6	4.2	4.0	5.8
lzop -6	1.5	4.0	1.1	3.7	1.4	4.4	0.9	2.3	1.0	2.6	2.7	3.4
bzip2 -9	2.8	10.0	2.0	8.3	3.4	10.0	1.0	4.3	1.8	5.7	5.3	8.0
xz -6	3.6	15.5	2.0	10.0	2.8	19.4	1.0	3.4	2.0	5.3	5.6	9.2
	Exercising											
gzip -6	2.1	6.4	1.6	5.5	2.2	6.9	1.3	4.0	1.9	5.2	4.3	6.0
lzop -6	1.3	3.8	1.0	3.6	1.4	4.4	1.0	2.8	1.0	2.8	2.8	3.5
bzip2 -9	2.7	9.4	1.9	7.7	3.9	10.0	1.4	5.5	2.9	8.7	6.6	9.3
xz -6	3.3	14.5	2.0	10.0	3.2	20.3	1.3	4.4	2.7	7.6	6.3	9.4

TABLE VI. WLAN UPLOAD THROUGHPUT IN MB/S

	ACC. WAVE		**BR. WAVE**		**ECG. WAVE**		**B2B. TIME**		**R2R. TIME**		**SUM. LOG**	
	BIN	**CSV**	**BIN**	**CSV**	**BIN**	**CSV**	**BIN**	**CSV**	**BIN**	**CSV**	**BIN**	**CSV**
	Sleeping											
Th.UUP	**1.87**	**1.96**	**1.48**	**1.91**	**1.86**	**1.95**	**0.03**	**0.10**	**0.10**	**0.32**	**1.60**	**1.70**
gzip -6	1.43	5.69	1.59	3.64	2.79	4.97	0.04	0.27	0.13	0.66	4.74	5.70
lzop -6	3.99	8.49	2.18	7.55	3.57	8.94	0.03	0.26	0.10	0.73	6.09	7.28
bzip2 -9	1.36	2.02	1.52	2.24	1.38	2.37	0.04	0.35	0.15	0.84	1.76	1.62
xz -6	0.31	0.34	0.66	0.26	0.27	0.27	0.03	0.18	0.13	0.34	0.47	0.44
	Exercising											
Th.UUP	**1.53**	**1.89**	**0.76**	**1.63**	**1.45**	**1.93**	**0.01**	**0.04**	**0.05**	**0.15**	**0.87**	**1.05**
gzip -6	1.48	2.45	0.80	3.79	1.60	4.65	0.01	0.11	0.08	0.48	1.79	2.26
lzop -6	1.83	6.60	0.71	5.00	1.80	7.68	0.01	0.11	0.05	0.37	2.04	3.05
bzip2 -9	1.49	1.94	0.73	1.95	1.55	2.21	0.02	0.14	0.11	0.64	1.43	1.44
xz -6	0.54	0.31	0.55	0.38	0.46	0.28	0.01	0.09	0.08	0.39	0.50	0.40

Table 7 shows the effective throughput on the WLAN interface for uncompressed downloads (Th.UDW) and the compressed downloads with decompression. The results show that the compressed downloads with decompression improve effective throughput relative to the uncompressed downloads in all cases, except for the B2B.TIME and R2R.TIME binary files. The best effective throughput is achieved by *gzip* and *xz*. These utilities achieve a relatively high compression ratio with fast decompression, whereas *lzop* does not appear as an attractive option due to its relatively low compression ratio.

Tables 8 and 9 show the energy efficiency in MB/J for the uncompressed and compressed uploads and downloads, respectively. Similarly to the effective throughput, the results show that the compressed uploads indeed may help reduce the energy consumed relative to the uncompressed uploads. *lzop* emerges as the most energy efficient alternative for the compressed uploads, offering improvements for both the binary and text files. The most energy-efficient transfers are observed for the SUM.LOG files. Downloads with decompression offer significant improvements in energy efficiency relative to the uncompressed downloads, regardless of the type of activity. *gzip* and *xz* emerge as the most energy efficient alternatives.

TABLE VII. WLAN DOWNLOAD THROUGHPUT IN MB/s

	ACC. WAVE		BR. WAVE		ECG. WAVE		B2B. TIME		R2R. TIME		SUM. LOG	
	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV
	Sleeping											
Th.UDW	**3.54**	**3.91**	**2.35**	**3.64**	**3.47**	**3.95**	**0.03**	**0.10**	**0.11**	**0.31**	**2.70**	**2.91**
gzip -6	11.78	24.94	4.45	16.85	10.58	23.44	0.04	0.36	0.07	0.98	14.34	17.94
lzop -6	7.32	16.70	3.45	14.23	6.70	18.05	0.03	0.27	0.08	0.74	9.99	12.40
bzip2 -9	4.35	14.18	3.74	9.63	6.35	13.76	0.04	0.42	0.01	1.27	7.80	7.98
xz -6	11.66	27.60	4.92	19.89	12.03	28.81	0.04	0.37	0.05	1.16	14.18	18.09
	Exercising											
Th.UDW	**2.39**	**3.59**	**0.88**	**2.71**	**2.20**	**3.63**	**0.01**	**0.03**	**0.05**	**0.16**	**1.10**	**1.40**
gzip -6	3.88	16.04	1.17	10.01	3.61	18.18	0.01	0.11	0.09	0.66	3.29	5.28
lzop -6	2.94	12.18	0.84	8.14	2.78	14.29	0.01	0.08	0.05	0.40	2.62	4.10
bzip2 -9	3.35	10.42	1.13	7.67	3.59	13.04	0.02	0.14	0.13	0.84	2.86	3.85
xz -6	4.10	17.78	1.28	11.63	4.24	23.86	0.01	0.12	0.11	0.74	3.96	5.67

TABLE VIII. WLAN UPLOAD ENERGY EFFICIENCY IN MB/J

	ACC. WAVE		BR. WAVE		ECG. WAVE		B2B. TIME		R2R. TIME		SUM. LOG	
	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV
	Sleeping											
EE.UUP	**2.04**	**2.13**	**1.80**	**2.12**	**2.08**	**2.03**	**0.06**	**0.20**	**0.19**	**0.52**	**1.83**	**1.91**
gzip -6	1.16	3.93	1.46	3.24	2.24	3.54	0.07	0.47	0.24	0.95	4.59	4.50
lzop -6	4.41	8.98	2.76	8.42	4.05	8.78	0.06	0.51	0.18	1.23	7.67	8.57
bzip2 -9	0.99	1.06	1.14	1.44	1.02	1.37	0.08	0.77	0.29	1.11	1.17	1.05
xz -6	0.19	0.17	0.44	0.19	0.17	0.17	0.06	0.21	0.20	0.27	0.27	0.25
	Exercising											
EE.UUP	**1.24**	**1.65**	**0.79**	**1.50**	**1.44**	**1.85**	**0.02**	**0.06**	**0.06**	**0.22**	**0.92**	**0.94**
gzip -6	1.40	6.95	0.89	6.20	2.08	11.26	0.03	0.17	0.11	0.79	2.83	4.08
lzop -6	1.63	6.24	0.80	5.22	1.94	8.05	0.02	0.15	0.06	0.59	2.40	3.10
bzip2 -9	1.47	8.18	1.06	8.20	1.87	12.86	0.03	0.21	0.15	1.03	2.36	3.42
xz -6	0.48	3.16	0.65	5.60	0.45	6.29	0.02	0.06	0.12	0.28	0.51	0.75

V. CONCLUSIONS

Based on the results of our analysis we develop the following guidelines for transferring mHealth data between personal devices and the cloud. When uploading the mHealth data, the low-complexity utilities such as *lzop* should be used for data from inertial sensors, accelerometers, as well as log files. Certain types of mHealth data such as time intervals between successive breaths and R-peaks should be uploaded uncompressed. Downloading compressed files with decompression almost always helps reduce latency and increase energy efficiency. The compression utilities such as *gzip* and *xz* outperform other utilities as they combine good compression ratios with fast decompression. We also demonstrated that the type of monitored activity impacts the effectiveness of the compression utilities. These findings may guide mHealth application developers in developing frameworks for optimizing data transfers between the personal devices and the cloud with potential to improve user experience, reduce energy requirement, and reduce required storage.

TABLE IX. WLAN DOWNLOAD ENERGY EFFICIENCY IN MB/J

	ACC. WAVE		BR. WAVE		ECG. WAVE		B2B. TIME		R2R. TIME		SUM. LOG	
	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV	BIN	CSV
	Sleeping											
EE.UDW	**3.40**	**3.84**	**2.27**	**3.28**	**3.21**	**3.78**	**0.04**	**0.12**	**0.13**	**0.41**	**2.59**	**3.00**
gzip -6	10.74	22.03	4.44	20.74	9.34	19.61	0.05	0.48	0.19	1.61	15.10	26.61
lzop -6	7.09	16.24	3.47	14.30	6.21	16.71	0.04	0.33	0.12	1.07	10.36	14.30
bzip2 -9	3.97	9.90	3.20	20.91	4.18	9.91	0.06	0.63	0.23	2.22	5.70	9.02
xz -6	8.72	19.96	4.56	34.94	9.52	20.33	0.05	0.55	0.22	1.75	15.18	31.40
	Exercising											
EE.UDW	**2.37**	**3.27**	**1.11**	**2.64**	**2.42**	**3.75**	**0.01**	**0.06**	**0.06**	**0.22**	**1.37**	**2.14**
gzip -6	4.44	15.84	1.66	11.21	4.82	18.35	0.02	0.21	0.11	1.06	4.85	10.59
lzop -6	3.06	11.64	1.12	8.66	3.19	15.15	0.01	0.15	0.06	0.60	3.48	6.90
bzip2 -9	3.13	7.99	1.51	9.28	3.46	8.69	0.02	0.29	0.16	1.54	4.49	8.78
xz -6	4.38	14.59	1.85	14.14	5.34	18.03	0.02	0.23	0.15	1.39	6.35	12.10

REFERENCES

[1] M. Milosevic, A. Milenkovic, and E. Jovanov, "mHealth@ UAH: computing infrastructure for mobile health and wellness monitoring," *XRDS: Crossroads, The ACM Magazine for Students*, vol. 20, no. 2, pp. 43–49, 2013.

[2] S. Kumar, W. J. Nilsen, A. Abernethy, A. Atienza, K. Patrick, M. Pavel, W. T. Riley, A. Shar, B. Spring, D. Spruijt-Metz, D. Hedeker, V. Honavar, R. Kravitz, R. Craig Lefebvre, D. C. Mohr, S. A. Murphy, C. Quinn, V. Shusterman, and D. Swendeman, "Mobile Health Technology Evaluation: The mHealth Evidence Workshop," *American Journal of Preventive Medicine*, vol. 45, no. 2, pp. 228–236, Aug. 2013.

[3] A. Milenkovic, C. Otto, and E. Jovanov, "Wireless Sensor Networks for Personal Health Monitoring: Issues and an Implementation," *Computer Communications*, vol. 29, no. 13–14, pp. 2521–2533, 2006.

[4] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

[5] "PhysioNet." [Online]. Available: http://www.physionet.org/. [Accessed: 08-Jul-2015].

[6] "BioHarness 3 - Wireless Professional Heart Rate Monitor & Physiological Monitor with Bluetooth," *Zephyr Technology Corporation*. [Online]. Available: http://zephyranywhere.com/products/bioharness-3/. [Accessed: 13-Jul-2015].

[7] B. Klika and C. Jordan, "High-intensity circuit training using body weight: Maximum results with minimal investment," *ACSM's Health & Fitness Journal*, vol. 17, no. 3, pp. 8–13, 2013.

[8] A. Milenkovic, A. Dzhagaryan, and M. Burtscher, "Performance and Energy Consumption of Lossless Compression/Decompression Utilities on Mobile Computing Platforms," in *Modeling, Analysis Simulation of Computer and Telecommunication Systems (MASCOTS), 2013 IEEE 21st International Symposium on*, 2013, pp. 254–263.

[9] A. Dzhagaryan, A. Milenković, and M. Burtscher, "Quantifying Benefits of Lossless Compression Utilities on Modern Smartphones," in *2015 24th International Conference on Computer Communication and Networks (ICCCN)*, 2015.

[10] "OnePlus One." [Online]. Available: https://oneplus.net/one. [Accessed: 12-Jul-2015].