A Review of Lossless Data Compression Algorithms

Review Article

Aditya Meharia
School of Computer Engineering
Kalinga Institute of Industrial Technology
Bhubaneswar, India 751024
adityameharia14@gmail.com

Junaid H. Rahim
School of Computer Engineering
Kalinga Institute of Industrial Technology
Bhubaneswar, India 751024
junaidrahim5a@gmail.com

April 25, 2020

Abstract

This work aims to provide an introduction to the domain of Data Compression in Information Theory and a comprehensive review of the existing literature in the field of algorithms for Lossless Data Compression. We identify and discuss the potential opportunities, barriers and the future scope of the field. We also review data compression methods used for text, image, video and audio data.

***K*eywords** Data Compression · Algorithms · Lossless Data Compression · Information Theory

Submitted to **Dr. S.K.S. Parashar**

1 Introduction

A rapid growth in modern communication technology led an explosion in the amount of data we transmit and store. Large files consume significant resources for transmission as well as storage. Due to this exponential increase in the size of the data we transmit, researchers developed algorithms that can be used to compress the data to save storage space as well as transmission time. Data Compression is a process by which we encode the input data into a representation that occupies fewer bits than the original input. This encoded representation is transmitted and decoded back to the original form at the destination. Data compression algorithms are broadly classified into two classes viz **Lossless Compression** and **Lossy Compression** algorithms. We will be only covering Lossless Data Compression algorithms in this review article.

1.1 History of Data Compression

The field of data compression gained huge significance in the 1970s after the surge in the usage of the internet. The need to reduce transmission time pushed computer scientists to find new ways to compress information. Although, the very earliest form of compression was Morse Code, invented in 1838, in Morse code the letters 'e' and 't' from the english language were given shorter codes as they have a high probability of occurrence.

Later with the advent of mainframe computers, Calude Shanon and Robert Fano invented Shanon-Fano coding in 1949[1], the algorithm assigns shorter codes to symbols with high probability resulting in a shorter way to represent the data. In 1952, David Huffman, one of the students of Robert Fano at MIT studying information theory took the option to write a term paper when given a choice between taking a final exam or writing a paper. Huffman was interested in finding the most efficient way to assign prefix codes to a set of symbols, after months of work Huffman published Huffman Coding in his paper "A Method for the Construction of Minimum-Redundancy Codes"[2], Huffman coding was an improvement over Shanon-Fano coding in terms of efficiency as it assured the assignment of the shortest possible codes to the given symbols. The early implementations of Shanon-Fano coding and Huffman coding were done using hardcoded codes, later in the 1970s, software compression was implemented and Huffman Codes were dynamically generated depending on the input data.

In 1977, Abraham Lempel and Jacob Ziv published[3] their groundbreaking LZ77 algorithm and later the LZ78 algorithm, these algorithms used a dictionary to compress data. The popular UNIX operating system used a compression utility based on LZW which was a slight modification of the LZ78 algorithm. Later the UNIX community adopted the DEFLATE based gzip and Burrows-Wheeler transform based bzip2 formats mostly due to their open source nature[4]. It was a beneficial decision in the long run as gzip and bzip2 have consistently given higher compression ratios compared to the LZW format.

In 1989, Phil Katz released the PKZIP format, later in 1993 Katz updated the format and named it PKZIP 2.0, he based it on the DEFLATE algorithm, the .zip format used so extensively in today's day is based on the PKZIP 2.0 format. ZIP and other DEFLATE based formats were extremely popular till the mid 1990s when new and improved formats began to emerge. In 1993, Eugene Roshal released his WinRAR utility which uses the proprietary RAR format. The RAR format is one of the most used formats to compress data and share it via the internet. In 1999, UNIX adopted the 7-zip or the .7z format, this was the first one capable enough to challenge the dominance of the .zip and .rar formats as .7z was not limited to just one compression algorithm, but could instead choose any of bzip2, LZMA, LAMA2 and PPMd algorithms among others.

1.2 Overview of Lossless Data Compression Techniques

Lossless Compression algorithms are a class of algorithms that can reproduce the original content from the encoded respresentation without any loss of information, the data before compression and after decompression is exactly the same. Lossless compression is used in a variety of fields where it is important that the original and decompressed information be the same. The GNU tool gzip uses lossless algorithms for the ZIP file format.

Lossless compression algorithms usually have a two step procedure.

1. A statistical model of the input data is generated. This usually assigns a probability of occurrence to pieces of input data. For example, if the input data is piece of text, then the model would be the probabilities of occurance of each alphabet
2. A coding system uses this model to map the data in a way that the pieces with high probability of occurrence are assigned a shorter code than those with a low probability of occurance

The probabalistic model is usually generated in two ways, a static way and an adaptive/dynamic way. In the static approach, the data is analysed and the probability model is generated before starting the encoding procedure, this is a modular and simple approach but doesn't perform well for heterogeneous data since the approach forces the use of a single model for the all the data. In the dynamic method, the model is updated while compressing the data. The encoder and decoder start with a trivial model in the initial state, thus performs poorly on initial data, but as the model adapts to the data, the performance improves. Most efficient compression techniques usually employ an adaptive model. There are various ways to achieve losseless compression namely Run Length Encoding (RLE), Lossless predictive coding (LPC), Entropy coding and Arithmetic coding etc.[5][6]

2 Prefix Codes and Entropy

A prefix code is a "code" system in which the codes given to each character is not the prefix of the code given to any other character i.e. it follows the prefix property [7]. For example $\{2, 42, 12\}$ is an example of a prefix system whereas $\{2, 42, 12, 21\}$ is not because '2' is the prefix of '21'.

Prefix codes are also known as prefix-free codes, prefix condition codes and instantaneous codes. They are uniquely decodable codes that is no two codes will have the same value on decoding. Prefix codes can be both fixed length and of variable length. It does not require between words to seperate them. Variable length preifx codes have been used extensibly in Huffman and Shannon coding and are still used in modern compression algorithms along with arithmetic coding.

Entropy denotes the randomness of the data that you are passing as input to the compression algorithm. That means the more random the text i.e. higher entropy is, the lesser you can compress it. It represents an absolute limit on the best possible lossless compression of any communication: treating messages to be encoded as a sequence of independent and identically distributed random variables. Shannon's source coding theorem shows that, the average length of the shortest possible representation to encode the messages in a given alphabet is expressed as follows

Given a random variable X, with possible outcomes x_i, each with probability $P_X(x_i)$, the entropy $H(X)$ of X, where b is the base of the logarithm is as follows:

$$H(X) = -\sum_{i=1}^{n} P_X(x_i) \log_b P_X(x_i) = \sum_{i=1}^{n} P_X(x_i) I_X(x_i) = E[I_X]$$

3 Shanon Coding

It is named after its creator **Claude Shanon**, the technique was used to prove Shanon's noiseless coding theorem in his 1948 article "A Mathematical Theory of Communication"[1]. Even though being suboptimal, the method was a first of its kind. This method is credited to have given rise to the entire field of Information Theory. Some of the most efficient compression algorithms today are usually an exntension of shanon's method

Shanon Coding is a method to generate prefix codes for a given piece of data. It is done using the occurrence probabilities of the pieces of data. First the probabilities p_i are arranged in descending order, then each piece is assigned a code which is the first l_i digits of binary representation of the cumulative probability till that piece of data.

Given that the probability of occurrence is p_i, the cumulative probability is expressed as

$$\sum_{k=0}^{i-1} p_k$$

where $l_i = \lceil \log_2 p_i \rceil$

It is a suboptimal algorithm, it does not give the lowest possible code word length.

The following is an example of assigning prefix codes to compress the string "lossless data compression"

i	a_i	p_i	$p_c = \sum_{k=0}^{i-1} p_k$	Binary Representation	$l_i = \lceil \log_2 p_i \rceil$	code
0	s	0.24	0.00	0.00000000...	2	00
1	o	0.12	0.24	0.00111101...	3	001
2	e	0.08	0.36	0.01011100...	3	010
3	<space>	0.08	0.44	0.01110000...	3	011
4	a	0.08	0.52	0.10000101...	3	100
5	l	0.08	0.60	0.10011001...	3	100
6	i	0.04	0.68	0.10101110...	4	1010
7	d	0.04	0.72	0.10111000...	4	1011
8	t	0.04	0.76	0.11000010...	4	1100
9	c	0.04	0.80	0.11001100...	4	1100
10	m	0.04	0.84	0.11010111...	4	1101
11	r	0.04	0.88	0.11100001...	4	1110
12	p	0.04	0.92	0.11101011...	4	1110
13	n	0.04	0.96	0.11110101...	4	1111

4 Huffman Coding

Named after its creator David A. Huffman. Although C.E. Shannon [1] and R.M.Fano [8] developed ensemble coding procedures to prove that the average number of binary digits required per message approaches from above the average amount of information per message,it was not optimum. Kraft [9] had derived a coding method which gives an average code length as close as possible to the ideal when the ensemble contains a finite number of members. However Huffman was able to derive a definte procedure for this. The output of the Huffman table given us a prefix-variable code table which consists of the source symbol and the encoded symbol.

Like Shannon coding, Huffman algorithm also tries to minimize the entropy by assisgning shortest codes to the charcters which occur most frequently. The algorithm works by creating a binary tree (using a min heap) which can have either leaf nodes or internal nodes. The leaf node contains the weight and the symbol whereas the internal nodes consists of weight and links to the two child nodes. The bit '0' is used to reprsent the left child of an internal nodes whereas the bit '1' is used to represent the right child.

Steps to build a Huffman Tree:-

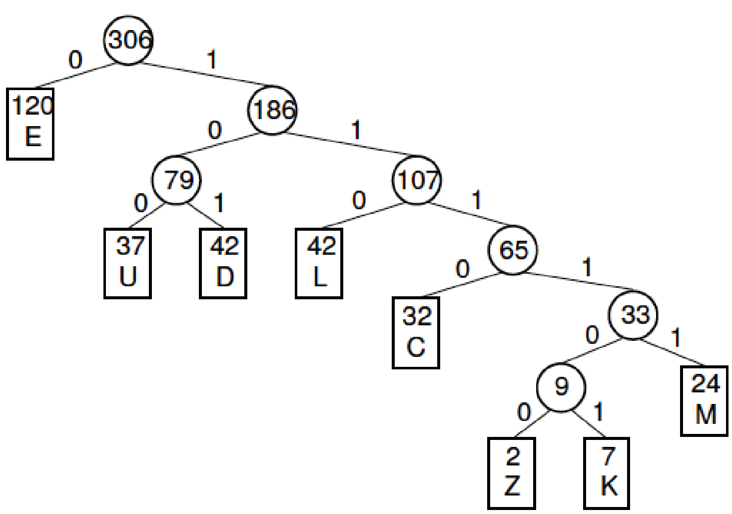
1. The process begins by traversing the input string and finding all the unique charcters along with their frequencies.
2. Then create a leaf node for each symbol and their frequencies(weight) and add build a min heap of all the leaf nodes.
3. Take the two nodes with the minimum weight and create a new internal node with the weight equal to the sum of the frequencies of the 2 nodes.Make the first extracted child as the left node and the second extracted child as the right node and add it to the min heap.
4. Repeat the steps until the heap contains only one node.

Letter freqency table

Letter	Z	K	M	C	U	D	L	E
Frequency	2	7	24	32	37	42	42	120

Huffman Code

Letter	Freq	Code	Bits
E	120	0	1
D	42	101	3
L	42	110	3
U	37	100	3
C	32	1110	4
M	24	11111	5
K	7	111101	6
Z	2	111100	6



Decoding the Huffman tree is very simple, traverse the tree node by node as each bit is read from the input stream (reaching a leaf node necessarily terminates the search for that particular byte value).

For example, decoding an encoded string can be done by looking at the bits in the coded string from left to right until a letter decoded. 10100101 ⇒ DEED

5 Lempel-Ziv(lz) Compression Methods

Also known as the LZ family,it initially consisted of LZ-77 and LZ-78 which was published by Abraham Lempel and Jacob Ziv in 1977[3] and 1978[10].Also known as LZ-1 and LZ-2 respectively,both are theoretically dictionary coders.These algorithms formed the basis for a lot of variations like LZW,LZSS,LZMA and also for a lot compression schemes like DEFLATE which has been discussed later in this article.

5.1 LZ-77 Algorithm

LZ77 algorithms achieve compression by replacing repeated occurrences of data with references to a copy of that data existing earlier within the uncompressed data stream. A match is encoded by a pair of numbers called a length-distance pair, which is like the statement "each of the next length characters is equal to the characters exactly distance characters behind it in the uncompressed stream".

To spot matches, the encoder must keep track of some amount of the recent data, like the last 2 kB, 4 kB, or 32 kB. The structure during which this data is held is named a sliding window , which is why LZ77 is usually called sliding-window compression. The encoder must keep this data to find matches, and therefore the decoder must keep this data to interpret the matches the encoder refers to. The larger the sliding window is, the longer back the encoder may look for creating references.

While encoding, for the search pointer to continue finding matched pairs after the end of the search window, all characters from the primary match at offset D and forward to the end of the search window must have matched input, and these are the (previously seen) characters that comprise one run unit of length LR, which must equal D. When search pointer proceeds past the search window and forward, as long as the run pattern repeats within the input, the search and input pointers are going to be in sync and match characters until the run pattern is interrupted. Then L characters had been matched in total, L > D, and therefore the code is [D, L, c].

Upon decoding [D, L, c], again, D = LR. When the primary LR characters are read to the output, this corresponds to one run unit appended to the output buffer. At this moment , the read pointer might be thought of as only needing to return int(L/LR) + (1 if L mod LR != 0) times to the beginning of that single buffered run unit, read LR characters (or maybe fewer on the last return), and repeat until all of the L characters are read. But mirroring the encoding process, since the pattern is repetitive, the read pointer need only trail in sync with the write pointer by a fixed distance which is equal to the run length LR until L characters are copied to output in total.

Pseudocode

while input not empty **do**

prefix : longest prefix of input that begins in window

if prefix exists **then**

j : distance to start of prefix

k : length of prefix

a : char following prefix in input

else j := 0

k := 0

a := first char of input

end if

output (j,k,a)

s := pop k + 1 chars from front of input

discard k + 1 chars from front of window

append s to back of window

repeat

5.2 LZ-78 Algorithm

The LZ78 is also a dictionary-based compression algorithm that maintains a dictionary. The encoded output consists of two elements: an index pertaining to the longest matching lexical entry and therefore the first non-matching symbol. The algorithm also adds the index and symbol pair to the dictionary. When the symbol is not yet found in the dictionary, the codeword has the index value 0 and it's added to the dictionary as well . With this method, the algorithm constructs the dictionary. LZ78 algorithm has the power to capture patterns and hold them indefinitely but it also features a serious drawback. The dictionary keeps growing forever without bound. There are a lot of methods to limit dictionary size. the easiest one is to stop adding entries and continue like a static dictionary coder or to throw the dictionary away and start from scratch after a certain number of entries has been reached[11]

Pseudocode

q : NIL;

While (there is input) **do**

J : next symbol from input;

If (qJ exists in the dictionary) **then**

q : qJ;

Else

Output (index(q), J);

Add qJ to the dictionary;

q : NIL;

end if

repeat

6 Arithmetic Coding

Arithmetic coding is a data compression technique that encodes data (the data string) by creating a code string which represents a fractional value on the number line between 0 and 1. The coding algorithm is symbolwise recursive; i.e., it operates upon and encodes (decodes) one data symbol per iteration or recursion. On each recursion, the algorithm successively partitions an interval of the number line between 0 and 1, and retains one of the partitions as the new interval. Thus, the algorithm successively deals with smaller intervals, and the code string, viewed as a magnitude, lies in each of the nested intervals. The data string is recovered by using magnitude comparisons on the code string to recreate how the encoder must have successively partitioned and retained each nested subinterval. Arithmetic coding differs considerably from the more familiar compression coding techniques, such as prefix (Huffman) codes. Also, it should not be confused with error control coding, whose object is to detect and correct errors in computer operations.

7 DEFLATE

DEFLATE is a lossless data compression file format that uses a combination of LZSS and Huffman coding. It was designed by Phil Katz, for version 2 of his PKZIP archiving tool. Deflate was later specified in RFC 1951 (1996). Katz also designed the original algorithm used to construct Deflate streams. This algorithm was patented as U.S. Patent 5,051,745, and assigned to PKWARE, Inc.[2][3] As stated in the RFC document, an algorithm producing Deflate files was widely thought to be implementable in a manner not covered by patents.[1] This led to its widespread use, for example in gzip compressed files and PNG image files, in addition to the ZIP file format for which Katz originally designed it.

Current Research Work

The current research work in Data Compression has shifted more towards the application part, where data compression is being applied in all sorts of fields like Deep Learning, Networking, Image Compression, Video and Audio Compression etc. We have discussed few papers which represent the research done in various domains to get the most out of data compression and make computing systems more efficient.

8 Tweet Classification By Data Compression [12]

The above mentioned paper proposes a compression based method for classification of tweets. They used the DEFLATE algorithm to compress the tweet and then evaluate and classify the given tweet according to its compressibility. The proposed method achieved higher accuracy when compared to the state of the art learning methods.

8.1 Proposed Method

The main problem was to classify the tweet according to the sentiment of the tweet, i.e classifying them into "positive" and "negative" classes. The algorithm was fed query strings and then slow it learns the difference by creating two tweet models M_n and M_p. Finally the algorithm calculates a classification score $f(x)$ which is then used to finally classify using a fixed threshold value.

8.2 Classification

There are 2 steps involved in the classification procedure. The first step calculated the compressibility of the tweet and the second step calculates the classification score.

The Compressibility scores are calculated as follows [12]

$$C_p = Z(M_p.x) - Z(M_p)$$
$$C_n = Z(M_n.x) - Z(M_n)$$

Where C_p and C_n are the compressibility scores. $M_p.x$ implies that x is appended to M_p and $Z(k)$ is the compressed size of the input k

And finally the classification score is calculated as follows

$$f(x) = \frac{C_p(x) + \gamma}{C_n(x) + \gamma}$$

where γ is a smoothing parameter. Also known as Laplace Smoothing.

8.3 Results

According to the results mentioned in the article, CTC performed statistically better than the state of the art methods. This method also applies to multi lingual tweets which gives it an edge over some of the other machine learning approaches.

This paper was an interesting application of the DEFLATE algorithm to classify tweets.

9 Energy Aware Lossless Data Compression [13]

This paper reports a rather different viewpoint on the whole compression domain. The energy required to send a bit via wireless transmission is close to 1000 times higher than the energy required for a regular 32 bit operation on a computer. The article reports the fact that compressing and decompressing information before and after transmission is more energy expensive compared to the case without any compression. The paper suggests solutions to this problem and they are able to achive an energy reduction of close to 51%.

9.1 Methodologies and Summary

The tests were done on a Compaq Personal Server codenamed "Skiff".

The energy required for compression and decompression are almost directly proportional to time required for executing. The energy required is observed to be more for aggressively compressed data due to the large number of memory references. Even though the energy requirement is proportional to the execution time, using the fastest algorithm for compression and decompression doesn't reduce the energy footprint. They were able to conclude the fact that reducing energy is not as simple as picking the fastest compression algorithm.

The energy requirements of the CPU and Network change drastically. They are extremely difficult to predict over a period of time. Thus software developers have to be aware of their hardware constraints and optimize accordingly to reduce energy footprint.

10 Lossless Compression of Already Compressed Textures [14]

The following cited paper investigates and proposes a lossless compression algorithm for rendering textures in graphics

Compressing textures allow the computer to render more textures due to smaller memory consumption, as the memory access. Compared to image compression methods like JPEG however, textures codecs are typically much less efficient, which is a problem when downloading the texture over a network or reading it from disk. Therefore, in this paper we investigate lossless compression of already compressed textures. By predicting compression parameters in the image domain instead of in the parameter domain, a more efficient representation is obtained compared to using general compression such as ZIP or LZMA.

11 Texture compression using low-frequency signal modulation [15]

A new lossy texture compression technique is presented in this paper that is suited to implementation on low-cost, low-bandwidth devices as well as more powerful rendering systems. It uses a representation that is based on the blending of two (or more) 'low frequency' signals using a high frequency but low precision modulation signal. Continuity of the low frequency signals helps to avoid block artifacts. Decompression costs are kept low through use of fixed-rate encoding and by eliminating indirect data access.

Some of the other interesting papers we found are cited below.

Towards Analysis-friendly Face Representation with Scalable Feature and Texture Compression [16]

On the Compressive Power of Boolean Threshold Autoencoders [17]

12 Conclusion and Future Prospects

In the presented review article we had an overview and simple examples of some of the most established methods in the domain of Lossless Data Compression. We also had a look at some of the modern research going on in the field. Almost every software system in function today has a component of compression and decompression to reduce the load and improve efficiency.

As we are moving towards a more data driven age, the amount of which users are creating data is exploding. In such scenarios, data compression stands at a very crucial juncture. Active research in this field will yield astonishing speed improvements in the current computing landscape.

References

[1] Claude E Shannon. A mathematical theory of communication. *Bell system technical journal*, 27(3):379–423, 1948.

[2] David A Huffman. A method for the construction of minimum-redundancy codes. *Proceedings of the IRE*, 40(9):1098–1101, 1952.

[3] Jacob Ziv and Abraham Lempel. A universal algorithm for sequential data compression. *IEEE Transactions on information theory*, 23(3):337–343, 1977.

[4] Michael Burrows and David J Wheeler. A block-sorting lossless data compression algorithm. 1994.

[5] PM Parekar and SS Thakare. Lossless data compression algorithm–a review. *International Journal of Computer Science & Information Technologies*, 5(1), 2014.

[6] P Yellamma and Narasimham Challa. Performance analysis of different data compression techniques on text file. *International Journal of Engineering Research & Technology (IJERT)*, 1(8):1–6, 2012.

[7] Jean Berstel and Dominique Perrin. *Theory of codes*. Academic Press, 1985.

[8] Robert M Fano. *The transmission of information*. Massachusetts Institute of Technology, Research Laboratory of Electronics . . . , 1949.

[9] Leon Gordon Kraft. *A device for quantizing, grouping, and coding amplitude-modulated pulses*. PhD thesis, Massachusetts Institute of Technology, 1949.

[10] Jacob Ziv and Abraham Lempel. Compression of individual sequences via variable-rate coding. *IEEE transactions on Information Theory*, 24(5):530–536, 1978.

[11] Christina Zeeh. The lempel ziv algorithm. In *URL: http://w3studi. informatik. uni-stuttgart. de/˜ zeehca/Seminar/LempelZivReport. pdf [accessed November 3, 2003]*, 2003.

[12] Kyosuke Nishida, Ryohei Banno, Ko Fujimura, and Takahide Hoshide. Tweet classification by data compression. In *Proceedings of the 2011 International Workshop on DETecting and Exploiting Cultural DiversiTy on the Social Web*, DETECT '11, page 29–34, New York, NY, USA, 2011. Association for Computing Machinery.

[13] Kenneth C. Barr and Krste Asanović. Energy-aware lossless data compression. *ACM Trans. Comput. Syst.*, 24(3):250–291, August 2006.

[14] Jacob Strom and Per Wennersten. Lossless compression of already compressed textures. In *Proceedings of the ACM SIGGRAPH Symposium on High Performance Graphics*, pages 177–182, 2011.

[15] Simon Fenney. Texture compression using low-frequency signal modulation. In *Proceedings of the ACM SIGGRAPH/EUROGRAPHICS Conference on Graphics Hardware*, HWWS '03, page 84–91, Goslar, DEU, 2003. Eurographics Association.

[16] Shurun Wang, Shiqi Wang, Wenhan Yang, Xinfeng Zhang, Shanshe Wang, Siwei Ma, and Wen Gao. Towards analysis-friendly face representation with scalable feature and texture compression. *arXiv preprint arXiv:2004.10043*, 2020.

[17] Avraham A Melkman, Sini Guo, Wai-Ki Ching, Pengyu Liu, and Tatsuya Akutsu. On the compressive power of boolean threshold autoencoders. *arXiv preprint arXiv:2004.09735*, 2020.

Review References

18. D. Benedetto, E. Caglioti, and V. Loreto. Language trees and zipping. Physical Review Letters, 88(4), 28 Jan. 2002.
19. A. Bratko, G. V. Cormack, B. Filipi˘c, T. R. Lynam, and B. Zupan. Spam filtering using statistical data compression models. Journal of Machine Learning Research, 7:2673–2698, 2006.
20. M. Burrows and D. J. Wheeler. A block-sorting lossless data compression algorithm. Technical Report SRC-RR-124, Digiral Systems Research Center, 1994.
21. R. Cilibrasi and P. Vit´anyi. Clustering by compression. IEEE Transactions on Information Theory, 51(4):1523–1545, 2005.
22. J. G. Cleary and I. H. Witten. Data compression using adaptive coding and partial string matching. IEEE Transactions on Communications, COM-32(4):396–402, 1984.
23. G. Cormack and R. N. S. Horspool. Data compression using dynamic markov modelling. The Computer Journal, 30(6):541–550, 1987.

24. K. Crammer, O. Dekel, J. Keshet, S. Shalev-Shwartz, and Y. Singer. Online passive-agressive algorithm. Journal of Machine Learning Research, 7:551–585, 2006.
25. M. Dredze, K. Crammer, and F. Pereira. Confidence-weighted linear classification. In Proceedings of 25th International Conference on Machine Learning, pages 264–271, 2008.
26. D. Irani, S. Webb, C. Pu, and K. Li. Study of trend-stuffing on twitter through text classification. In Proceedings of 7th Annual Collaboration, Electronic messaging, Anti-Abuse and Spam Conference, 2010.
27. H. Kwak, C. Lee, H. Park, and S. Moon. What is twitter, a social network or a news media? In Proceedings of 19th International Conference on World Wide Web, pages 591–600, 2010.
28. M. Li, X. Chen, X. Li, B. Ma, and P. M. B. Vit´anyi. The similarity metric. IEEE Transactions on Information Theory, 50(12):3250–3264, 2004.
29. M. Li and P. Vit´anyi. An Introduction to Kolmogorov Complexity and Its Applications. Springer, 2nd edition, 1997.
30. Y. Marton, N. Wu, and L. Hellerstein. On compression-based text classification. In Proceedings of the 27th European Conference on Information Retrieval, pages 300–314, 2005.
31. T. Sakaki, M. Okazaki, and Y. Matsuo. Earthquake shakes twitter users: Real-time event detection by social sensors. In Proceedings of 19th International Conference on World Wide Web, pages 851–860, 2010.
32. B. Sriram, D. Fuhry, and M. Demirbas. Short text classification in twitter to improve information filtering. In Proceedings of 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 841–842, 2010.
33. I. H. Witten, A. Moffat, and T. C. Bell. Managing Gigabytes: compressing and indexing documents and images. Morgan Kaufmann, 2nd edition, 1999.
34. J. Ziv and A. Lempel. A universal algorithm for sequential data compression. IEEE Transactions on Information Theory, IT-23(3):337–343, 1977.
35. Advanced RISC Machines Ltd (ARM). Writing Efficient C for ARM, Jan. 1998. Application Note 34.
36. T. M. Austin and D. C. Burger. SimpleScalar version 4.0 release. Tutorial in conjunction with 34th Annual International Symposium on Microarchitecture, Dec. 2001.
37. T. Bell and D. Kulp. Longest match string searching for Ziv-Lempel compression. Technical Report 06/89, Department of Computer Science, University of Canterbury, New Zealand, 1989.
38. T. Bell, M. Powell, J. Horlor, and R. Arnold. The Canterbury Corpus. http://www.corpus.canterbury.ac.nz/.
39. T. Bell, I. H. Witten, and J. G. Cleary. Modeling for text compression. ACM Computing Surveys, 21(4):557–591, 1989.
40. J. Bilmes, K. Asanovic, C.-W. Chin, and J. Demmel. Op- ´ timizing matrix multiply using PHiPAC: a portable, highperformance, ANSI C coding methodology. In 11th ACM International Conference on Supercomputing, July 1997.
41. D. C. Burger and T. M. Austin. The SimpleScalar tool set, version 2.0. Technical Report CS-TR-97-1342, University of Wisconsin, Madison, June 1997.
42. M. Burrows and D. J. Wheeler. A block-sorting lossless data compression algorithm. Technical Report 124, Digital Systems Research Center, May 1994.
43. J. Gailly and M. Adler. zlib. http://www.gzip.org/zlib.
44. J. Gailly, Maintainer. comp.compression Internet newsgroup: Frequently Asked Questions, Sept. 1999.
45. J. Gilchrist. Archive comparison test. http://compression.ca.
46. P. J. Havinga. Energy efficiency of error correction on wireless systems. In IEEE Wireless Communications and Networking Conference, Sept. 1999.
47. J. Hicks et al. Compaq personal server project, 1999. http://crl.research.compaq.com /projects/personalserver/default.htm.
48. B. C. Housel and D. B. Lindquist. Webexpress: a system for optimizing web browsing in a wireless environment. In Proceedings of the Second Annual International Conference on Mobile Computing and Networking, 1996.
49. J. J. Hunt, K.-P. Vo, and W. F. Tichy. An empirical study of delta algorithms. In Software configuration management: ICSE 96 SCM-6 Workshop. Springer, 1996.

50. Hyperspace Communications, Inc. Mod gzip. http://www.ehyperspace.com /htmlonly/products/mod gzip.html.
51. Intel Corporation. SA-110 Microprocessor Technical Reference Manual, December 2000.
52. Intel Corporation. Intel StrongARM SA-1110 Microprocessor Developer's Manual, October 2001.
53. V. Jacobson. RFC 1144: Compressing TCP/IP headers for low-speed serial links, Feb. 1990.
54. K. Jamieson. Implementation of a power-saving protocol for ad hoc wireless networks. Master's thesis, Massachusetts Institute of Technology, Feb. 2002.
55. P. Jannesen et. al. (n)compress. available, among other places, in Redhat 7.2 distribution of Linux.
56. K. Koskelin, K. Barr, and K. Asanovic. Eprof: An en- ´ ergy profiler for the iPaq. In 2nd Annual Student Oxygen Workshop. MIT Project Oxygen, 2002.
57. R. Krashinsky. Efficient web browsing for mobile clients using HTTP compression. Technical Report MIT-LCSTR-882, MIT Lab for Computer Science, Jan. 2003.
58. J. Lilley, J. Yang, H. Balakrishnan, and S. Seshan. A unified header compression framework for low-bandwidth links. In 6th ACM MOBICOM, Aug. 2000.
59. Lycos. Lycos 50, Sept. 2002. Top 50 searches on Lycos for the week ending September 21, 2002.
60. A. Miyoshi, C. Lefurgy, E. V. Hensbergen, R. Rajamony, and R. Rajkumar. Critical power slope: Understanding the runtime effects of frequency scaling. In International Conference on Supercomputing, June 2002.
61. J. C. Mogul. Trace-based analysis of duplicate suppression in HTTP. Technical Report 99.2, Compaq Computer Corporation, Nov. 1999.
62. J. C. Mogul, F. Douglis, A. Feldmann, and B. Krishnamurthy. Potential benefits of delta encoding and data compression for HTTP. Technical Report 97/4a, Compaq Computer Corporation, Dec. 1997.
63. J. Montanaro et al. A 160-mhz, 32-b, 0.5-w CMOS RISC microprocessor. IEEE Journal of Solid-State Circuits, 31(11), Nov. 1996.
64. N. Motgi and A. Mukherjee. Network conscious text compression systems (NCTCSys). In Proceedings of International Conference on Information and Theory: Coding and Computing, 2001.
65. A. Muthitacharoen, B. Chen, and D. Mazi'eres. A lowbandwidth network file system. In Proceedings of the 18th ACM Symposium on Operating Systems Principles (SOSP '01), pages 174–187, Chateau Lake Louise, Banff, Canada, October 2001.
66. Nielsen NetRatings Audience Measurement Service. Top 25 U.S Properties; Week of Sept 15th., Sept. 2002.
67. M. F. Oberhumer. LZO. http://www.oberhumer.com/opensource/lzo/.
68. A. Peymandoust, T. Simuni ˇ c, and G. D. Micheli. Low ´ power embedded software optimization using symbolic algebra. In Design, Automation and Test in Europe, 2002.
69. J. Santos and D. Wetherall. Increasing effective link bandwidth by suppressing replicated data. In USENIX Annual Technical Conference, June 1998.
70. K. Sayood. Introduction to data compression. Morgan Kaufman Publishers, second edition, 2002.
71. J. Seward. bzip2. http://www.spec.org /osg/cpu2000/CINT2000/256.bzip2/docs/256.bzip2.html.
72. J. Seward. e2comp bzip2 library. http://cvs.bofh.asn.au/e2compr/index.html.
73. A. Shacham, B. Monsour, R. Pereira, and M. Thomas. RFC 3173: IP payload compression protocol, Sept. 2001.
74. D. Shkarin. PPMd. ftp://ftp.elf.stuba.sk/pub/pc/pack/ppmdi1.rar.
75. A. Sinha, A. Wang, and A. Chandrakasan. Algorithmic transforms for efficient energy scalable computation. In IEEE International Symposium on Low Power Electronics and Design, August 2000.
76. Standard Performance Evaluation Corporation. CPU2000, 2000.
77. C. N. Taylor and S. Dey. Adaptive image compression for wireless multimedia communication. In IEEE International Conference on Communication, June 2001.
78. A. Tridgell. Efficient Algorithms for Sorting and Synchronization. PhD thesis, Australian National University, Apr. 2000.
79. T. Simuni ˇ c, L. Benini, and G. D. Micheli. Energy- ´ efficient design of battery-powered embedded systems. In IEEE International Symposium on Low Power Electronics and Design, 1999.

80. T. Simuni ˘ c, L. Benini, G. D. Micheli, and M. Hans. ´ Source code optimization and profiling of energy consumption in embedded systems. In International Symposium on System Synthesis, 2000.
81. M. A. Viredaz and D. A. Wallach. Power evaluation of Itsy version 2.4. Technical Report TN-59, Compaq Computer Corporation, February 2001.
82. H. Yang, G. R. Gao, A. Marquez, G. Cai, and Z. Hu. Power and energy impact of loop transformations. In Workshop on Compilers and Operating Systems for Low Power 2001, Parallel Architecture and Compilation Techniques, Sept. 2001.
83. BEERS, A., AGRAWALA, M., AND CHADDA, N. 1996. Rendering from Compressed Textures. In Proceedings of ACM SIGGRAPH 96, 373–378.
84. BPTC, 2010. ARB texture compression bptc. Available online: www.opengl.org/registry/specs/ARB/texture compression bptc.txt.
85. CAMPBELL, G., DEFANTI, T. A., FREDERIKSEN, J., JOYCE, S. A., LESKE, L. A., LINDBERG, J. A., AND SANDIN, D. J. 1986. Two Bit/Pixel Full Color Encoding. In Computer Graphics (Proceedings of ACM SIGGRAPH 86), 215–223.
86. DELP, E. J., AND MITCHELL, O. R. 1979. Image Compression using Block Truncation Coding. IEEE Transactions on Communications 2, 9, 1335–1342.
87. FENNEY, S. 2003. Texture Compression using Low-Frequency Signal Modulation. In Graphics Hardware, ACM Press, 84–91. INADA, T., AND MCCOOL, M. 2006. Compressed Lossless Texture Representation and Caching. In Graphics Hardware, 111– 120.
88. IOURCHA, K., NAYAK, K., AND HONG, Z., 1999. System and Method for Fixed-Rate Block-Based Image Compression with Inferred Pixel Values. US Patent 5,956,431.
89. JPEG, 2000. JPEG 2—ISO/IEC 15444-1:2005. Available online:http://www.jpeg.org/jpeg2000/.
90. KNITTEL, G., SCHILLING, A. G., KUGLER, A., AND STRASSER, W. 1996. Hardware for Superior Texture Performance. Computers and Graphics, 20, 4, 475–481.
91. MICROSOFT, 2006. HD Photo. Available online: http:/www.microsoft.com/windows/windowsmedia/forpros/wmphoto/default.aspx.
92. OWENS, J. D. 2005. Streaming Architectures and Technology Trends. In GPU Gems 2. Addison-Wesley, 457–470.
93. RASMUSSON, J., STROM¨ , J., WENNERSTEN, P., DOGGETT, M., AND AKENINE-MOLLER ¨ , T. 2010. Texture Compression of Light Maps using Smooth Profile Functions. In HighPerformance Graphics, 143–152.
94. STROM¨ , J., AND AKENINE-MOLLER ¨ , T. 2005. iPACKMAN: High-Quality, Low-Complexity Texture Compression for Mobile Phones. In Graphics Hardware, 63–70.
95. STROM¨ , J., AND PETTERSSON, M. 2007. ETC2: Texture Compression using Invalid Combinations. In Graphics Hardware, 49–54.
96. SUEHRING ¨ , K. 2009. JM Software H.264/AVC. http://iphome.hhi.de/suehring/tml/. TORBORG, J., AND KAJIYA, J. 1996. Talisman: Commodity Realtime 3D Graphics for the PC. In Proceedings of SIGGRAPH, 353–364.
97. VAN WAVEREN, J., 2006. Real-Time Texture Streaming and Decompression. Id Software Technical Report, available at http://software.intel.com/file/17248/.
98. WEINBERGER, M., SEROUSSI, G., AND SAPIRO, G. 1996. LOCO-I: A Low Complexity, Context-Based, Lossless Image Compression Algorithm. In Proc. IEEE Data Compression Conference, Snowbird, Utah, March-April 1996.
99. WHEELER, F., 1996. Adaptive Arithmetic Coding Source Code. available at http://www.cipr.rpi.edu/wheeler/ac/.
100. WITTEN, I. H., NEAL, R. M., AND CLEARY, J. G. 1987. Arithmetic Coding for Data Compression. Communications of the ACM 30, 6.
101. Edwin Catmull. “Computer Display of Curved Surfaces”, Proc. IEEE Conf. Computer Graphics, Pattern Recognition, and Data Structures May 1975, 11–17.
102. Andrew C. Beers, Maneesh Agrawala, and Navin Chadda. “Rendering from Compressed Textures”, Computer Graphics, Proc. SIGGRAPH 7(3), Aug.1996, 373–378

103. James Kajiya, Ivan Sutherland, and Edward Cheadle. "A Random-Access Video Frame Buffer", Proc. IEEE Computer Graphics, Pattern Recognition, and Data Structures May 1975, 1–6.
104. Paul Heckbert. "Color Image Quantisation for Frame Buffer Display", Computer Graphics 16(3), July 1982, 297–307.
105. Xiaolin Wu. "Color Quantization by Dynamic Programming and Principal Analysis", ACM Transactions on Graphics 11(4), Oct. 1992, 348–372.
106. Lance Williams. "Pyramidal Parametrics", Computer Graphics 7(3), July 1983, 1–11.
107. E. Delp and O. Mitchell. "Image Compression Using Block Truncation Coding", IEEE Trans. on Communications. Vol.COM-2 (9), Sept. 1979, 1335–1342.
108. Graham Campbell et al. "Two bit/pixel full color encoding", Computer Graphics 20(4), August 1986, 215–223.
109. G. Knittel, A. Schilling, A. Kugler, and W. Strasser. "Hardware for Superior Texture Performance", Proceedings of the 10th Eurographics Workshop on Graphics Hardware 1995, 33–39.
110. Konstantine Iourcha, Krishna Nayak, and Zhou Hong. "System and Method for Fixed-Rate Block-Based Image Compression with Inferred Pixel Values", US Patent 5,956,431.
111. L. Levkovich-Maslyuk, P. G. Kalyuzhny, and A. Zhirkov. "Texture Compression with Adaptive Block Partitions", ACM Multimedia 2000 Nov. 2000.
112. A.V. Pereberin. "Hierarchical Approach for Texture Compression", Proceedings of GraphiCon '99 1999,195–199.
113. Denis Ivanov and Yevgeniy Kuzmin. "Color Distribution - A New Approach to Texture Compression", Computer Graphics Forum 19(3), August 2000, 283–289.
114. Eric Stollnitz, Tony DeRose, and David Salesin. "Wavelets for Computer Graphics. Theory and Applications", ISBN 1-55860-375-1
115. Wim Sweldens and Peter Shroeder. "Building your own Wavelets at Home", Journal Technical Report 1995:5, Industrial Mathematics Initiative, Department of Mathematics, University of South Carolina
116. Press, Teukolsky, Vettering, and Flannery. "Numerical Recipes in C", ISBN 0-521-43108-5
117. http://sqez.home.att.net/thumbs/Thumbnails.html
118. G. K. Wallace, "The JPEG still picture compression standard," IEEE Transactions on Consumer Electronics, vol. 38, no. 1, pp. xviii–xxxiv, 1992.
119. M. Rabbani, "JPEG2000: Image compression fundamentals, standards and practice," Journal of Electronic Imaging, vol. 11, no. 2, p. 286, 2002.
120. T. Wiegand, G. J. Sullivan, G. Bjontegaard, and A. Luthra, "Overview of the H. 264/AVC video coding standard," IEEE Transactions on Circuits and Systems for Video Technology, vol. 13, no. 7, pp. 560–576, 2003.
121. G. J. Sullivan, J.-R. Ohm, W.-J. Han, and T. Wiegand, "Overview of the high efficiency video coding (HEVC) standard," IEEE Transactions on Circuits and Systems for Video Technology, vol. 22, no. 12, pp. 1649– 1668, 2012.
122. A. Mohan, K. Gauen, Y.-H. Lu, W. W. Li, and X. Chen, "Internet of video things in 2030: A world with many cameras," in IEEE International Symposium on Circuits and Systems. IEEE, 2017, pp. 1–4.
123. L.-Y. Duan, V. Chandrasekhar, J. Chen, J. Lin, Z. Wang, T. Huang, B. Girod, and W. Gao, "Overview of the MPEG-CDVS standard," IEEE Transactions on Image Processing, vol. 25, no. 1, pp. 179–194, 2015.
124. L.-Y. Duan, Y. Lou, Y. Bai, T. Huang, W. Gao, V. Chandrasekhar, J. Lin, S. Wang, and A. C. Kot, "Compact descriptors for video analysis: The emerging MPEG standard," IEEE MultiMedia, vol. 26, no. 2, pp. 44–54, 2018.
125. L.-Y. Duan, J. Liu, W. Yang, T. Huang, and W. Gao, "Video coding for machines: A paradigm of collaborative compression and intelligent analytics," arXiv preprint arXiv:2001.03569, 2020.
126. Y. Li, C. Jia, S. Wang, X. Zhang, S. Wang, S. Ma, and W. Gao, "Joint rate-distortion optimization for simultaneous texture and deep feature compression of facial images," in 2018 IEEE Fourth International Conference on Multimedia Big Data. IEEE, 2018, pp. 1–5.

127. S. Wang, S. Wang, X. Zhang, S. Wang, S. Ma, and W. Gao, “Scalable facial image compression with deep feature reconstruction,” in 2019 IEEE International Conference on Image Processing. IEEE, 2019, pp. 2691–2695.

128. I. Recommendation, “Generic coding of moving pictures and associated audio information: Video,” 1995.

129. J. Pfaff, B. Stallenberger, M. Schafer, P. Merkle, P. Helle, T. Hinz, H. Schwarz, D. Marpe, and T. Wiegand, “CE3: Affine linear weighted intra prediction (CE3–4.1 CE3–4.2),” in document JVET-N0217, in Proc. of 14th JVET meeting, 2019.

130. J. An, Y. Chen, K. Zhang, H. Huang, Y. Huang, and S. Lei, “Block partitioning structure for next generation video coding,” MPEG doc. m37524 and ITU-T SG16 Doc. COM16–C966, 2015.

131. M. Wang, J. Li, L. Zhang, K. Zhang, H. Liu, S. Wang, S. Kwong, and S. Ma, “Extended coding unit partitioning for future video coding,” IEEE Transactions on Image Processing, 2019.

132. S. Lin, H. Chen, H. Zhang, S. Maxim, H. Yang, and J. Zhou, “Affine transform prediction for next generation video coding,” MPEG doc. m37525 and ITU-T SG16 Doc. COM16–C1016, 2015.

133. X. Chen, J. An, and J. Zheng, “EE3: Decoder-side motion vector refinement based on bilateral template matching,” in Joint Video Exploration Team of ITU-T SG16 WP3 and ISO/IEC JTC1/SC29/WG11, JVETE0052, 5th Meeting, 2017.

134. X. Zhao, J. Chen, and M. Karczewicz, “Mode-dependent non-separable secondary transform,” ITU-T SG16/Q6 Doc. COM16–C1044, 2015.

135. B. Li, H. Li, L. Li, and J. Zhang, “Lambda domain rate control algorithm for high efficiency video coding,” IEEE Transactions on Image Processing, vol. 23, no. 9, pp. 3841–3854, 2014.

136. J. Chao, R. Huitl, E. Steinbach, and D. Schroeder, “A novel rate control framework for SIFT/SURF feature preservation in H. 264/AVC video compression,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 25, no. 6, pp. 958–972, 2014.

137. T. Huang, “Surveillance video: The biggest big data,” Computing Now, vol. 7, no. 2, pp. 82–91, 2014.

138. M. Paul, W. Lin, C.-T. Lau, and B.-S. Lee, “Explore and model better i-frames for video coding,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 21, no. 9, pp. 1242–1254, 2011.

139. X. Zhang, T. Huang, Y. Tian, and W. Gao, “Background-modeling-based adaptive prediction for surveillance video coding,” IEEE Transactions on Image Processing, vol. 23, no. 2, pp. 769–784, 2013.

140. F. Chen, H. Li, L. Li, D. Liu, and F. Wu, “Block-composed background reference for high efficiency video coding,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 27, no. 12, pp. 2639– 2651, 2016.

141. H. Yue, X. Sun, J. Yang, and F. Wu, “Cloud-based image coding for mobile devicestoward thousands to one compression,” IEEE Transactions on Multimedia, vol. 15, no. 4, pp. 845–857, 2013.

142. Z. Shi, X. Sun, and F. Wu, “Photo album compression for cloud storage using local features,” IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 4, no. 1, pp. 17–28, 2014.

143. L. Zhao, Z. He, W. Cao, and D. Zhao, “Real-time moving object segmentation and classification from hevc compressed surveillance video,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 28, no. 6, pp. 1346–1357, 2016.

144. D. Edmundson and G. Schaefer, “An overview and evaluation of JPEG compressed domain retrieval techniques,” in Proceedings ELMAR-2012. IEEE, 2012, pp. 75–78.

145. G. Toderici, S. M. O’Malley, S. J. Hwang, D. Vincent, D. Minnen, S. Baluja, M. Covell, and R. Sukthankar, “Variable rate image compression with recurrent neural networks,” ICLR, 2016.

146. J. Balle, V. Laparra, and E. Simoncelli, “End-to-end optimized image ´ compression,” in International Conference on Learning Representations, 2017.

147. J. Balle, D. Minnen, S. Singh, S. J. Hwang, and N. Johnston, “Variational ´image compression with a scale hyperprior,” in International Conference on Learning Representations, 2018.

148. G. Lu, W. Ouyang, D. Xu, X. Zhang, C. Cai, and Z. Gao, “DVC: An end-to-end deep video compression framework,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 11 006–11 015.

149. A. Redondi, L. Baroffio, M. Cesana, and M. Tagliasacchi, “Compressthen-analyze vs. analyze-then-compress: Two paradigms for image analysis in visual sensor networks,” in IEEE International Workshop on Multimedia Signal Processing. IEEE, 2013, pp. 278–282.

150. W. Liu, J. Wang, R. Ji, Y.-G. Jiang, and S.-F. Chang, “Supervised hashing with kernels,” in 2012 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2012, pp. 2074–2081.

151. V. Chandrasekhar, G. Takacs, D. Chen, S. S. Tsai, J. Singh, and B. Girod, “Transform coding of image feature descriptors,” in Visual Communications and Image Processing 2009, vol. 7257. International Society for Optics and Photonics, 2009, p. 725710.

152. H. Jegou, M. Douze, and C. Schmid, “Product quantization for nearest neighbor search,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 1, pp. 117–128, 2010.

153. A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in Neural Information Processing Systems, 2012, pp. 1097–1105.

154. K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in International Conference on Learning Representations, 2015.

155. F. Schroff, D. Kalenichenko, and J. Philbin, “Facenet: A unified embedding for face recognition and clustering,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 815– 823.

156. L. Ding, Y. Tian, H. Fan, Y. Wang, and T. Huang, “Rate-performanceloss optimization for inter-frame deep feature coding from videos,” IEEE Transactions on Image Processing, vol. 26, no. 12, pp. 5743–5757, 2017.

157. L. Ding, Y. Tian, H. Fan, C. Chen, and T. Huang, “Joint coding of local 11 and global deep features in videos for visual search,” IEEE Transactions on Image Processing, vol. 29, pp. 3734–3749, 2020.

158. H. Zhu, M. Long, J. Wang, and Y. Cao, “Deep hashing network for efficient similarity retrieval,” in Thirtieth AAAI Conference on Artificial Intelligence, 2016.

159. S. Wang, W. Yang, and S. Wang, “End-to-end facial deep learning feature compression with teacher-student enhancement,” arXiv preprint arXiv:2002.03627, 2020.

160. Z. Chen, K. Fan, S. Wang, L. Duan, W. Lin, and A. C. Kot, “Toward intelligent sensing: Intermediate deep feature compression,” IEEE Transactions on Image Processing, vol. 29, pp. 2230–2243, 2020.

161. Y. Hu, S. Yang, W. Yang, L.-Y. Duan, and J. Liu, “Towards coding for human and machine vision: A scalable image coding approach,” arXiv preprint arXiv:2001.02915, 2020.

162. S. Xia, K. Liang, W. Yang, L.-Y. Duan, and J. Liu, “An emerging coding paradigm VCM: A scalable coding approach beyond feature and signal,” arXiv preprint arXiv:2001.03004, 2020.

163. Y. Lou, L. Duan, S. Wang, Z. Chen, and W. Gao, “Front-end smart visual sensing and back-end intelligent analysis: A unified infrastructure for economizing the visual system of city brain,” IEEE Journal on Selected Areas in Communications, vol. PP, no. 99, pp. 1–1, 2019.

164. L. Duan, Y. Lou, S. Wang, W. Gao, and Y. Rui, “AI-oriented largescale video management for smart city: Technologies, Standards, and Beyond,” IEEE MultiMedia, vol. 26, no. 2, pp. 8–20, April 2019.

165. G. Wen, Y. Tian, T. Huang, S. Ma, and X. Zhang, “The IEEE 1857 standard: Empowering smart video surveillance systems,” Intelligent Systems IEEE, vol. 29, no. 5, pp. 30–39, 2014.

166. Y. Lou, L. Duan, Y. Luo, Z. Chen, T. Liu, S. Wang, and W. Gao, “Towards efficient front-end visual sensing for digital retina: A modelcentric paradigm,” IEEE Transactions on Multimedia, 2020.

167. C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, “Inception-v4, Inception-Resnet and the impact of residual connections on learning,” in Thirty-first AAAI conference on artificial intelligence, 2017.

168. B. Gary, R. Manu, B. Tamara, and L. Erik, “Labeled faces in the wild: A database for studying face recognition in unconstrained environments,” University of Massachusetts, Amherst, Tech. Rep. 07-49, October 2007.

169. Q. Cao, L. Shen, W. Xie, O. Parkhi, and A. Zisserman, “VGGFace2: A dataset for recognising faces across pose and age,” in International Conference on Automatic Face and Gesture Recognition, 2018.

170. S. Ma, X. Zhang, C. Jia, Z. Zhao, S. Wang, and S. Wanga, “Image and video compression with neural networks: A review,” IEEE Transactions on Circuits and Systems for Video Technology, 2019.

171. X. Glorot and Y. Bengio, “Understanding the difficulty of training deep feedforward neural networks,” in Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics, 2010, pp. 249–256.

172. D. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

173. K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, “Joint face detection and alignment using multitask cascaded convolutional networks,” IEEE Signal Processing Letters, vol. 23, no. 10, pp. 1499–1503, 2016.

174. H. Jgou, M. Douze, and C. Schmid, “Product quantization for nearest neighbor search,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 1, pp. 117–128, Jan 2011.
175. T. Ge, K. He, Q. Ke, and J. Sun, “Optimized product quantization,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 36, no. 4, pp. 744–755, April 2014.
176. W. Liu, J. Wang, R. Ji, Y. Jiang, and S. Chang, “Supervised hashing with kernels,” in 2012 IEEE Conference on Computer Vision and Pattern Recognition, June 2012, pp. 2074–2081.
177. D. H. Ackley, G. H. Hinton, and T. J. Sejnowski, “A learning algorithm for Boltzmann machines,” Cognitive Science, vol. 9, pp. 147–169, 1985.
178. P. Baldi and K. Hornik, “Neural networks and principal component analysis: Learning from examples without local minima,” Neural Networks, vol. 2, pp. 53–38, 1989.
179. G. E. Hinton and R. R. Salakhutdinov, “Reducing the dimensionality of data with neural networks,” Science, vol, 313, pp. 504–507, Jul. 2006.
180. P. Baldi, “Autoencoders, unsupervised learning, and deep architectures,” JMLR: Workshop and Conference Proceedings, vol. 27, pp. 37–50, 2012.
181. D. P. Kingma and M, Welling, “Auto-encoding variational Bayes,” arXiv:1312.6114, 2013.
182. C. Doersch, “Tutorial on variational autoencoders,” arXiv:1606.05908, 2016.
183. M. Tschannen, O. Bachem, and M. Lucic. “Recent advances in autoencoder-based representation learning,” arXiv:1812.05069, 2018.
184. R. G´omez-Bombarelli, J. N. Wei, D. Duvenaud, J. M. Hern´andez-Lobato, et al., “Automatic chemical design using a data-driven continuous representation of molecules,” ACS Central Science, vol. 4, no. 2, pp. 268–276, 2018.
185. O. Delalleau and Y. Bengio, “Shallow vs. deep sum-product networks,” In Advances in Neural Information Processing Systems, pp. 666-674, 2011.12
186. G. F. Montufar, R. Pascanu, K. Cho, and Y. Bengio. “On the number of linear regions of deep neural networks,” In Advances in Neural Information Processing Systems, pp. 2924-2932, 2014.
187. S. An, M. Bennamoun, and F. Boussaid, “On the compressive power of deep rectifier networks for high resolution representation of class boundaries,” in arXiv:1708.07244v1, 2017.
188. C. Zhang, S. Bengio, M. Hardt, B. Recht, and O. Vinyals, “Understanding deep learning requires rethinking generalization,” in Proc. ICLR 2017 (arXiv:1611.03530), 2017.
189. S. A. Kauffman, “Metabolic stability and epigenesis in randomly constructed genetic nets,” J. Theoret. Biol., vol. 22, no. 3, pp. 437–467, Mar. 1969.
190. T. Akutsu, Algorithms for Analysis, Inference, and Control of Boolean Networks. Singapore: World Scientific, 2018.
191. D. Cheng, H. Qi, and Z. Li, Analysis and Control of Boolean Networks: A Semi-tensor Product Approach.
192. F. Li, “Pinning control design for the stabilization of Boolean networks,” IEEE Trans. Neural Netw. Learning Syst., vol. 27, no. 7, pp. 1585–1590, 2016.
193. Y. Liu, L. Sun, J. Lu and J. Liang, “Feedback controller design for the synchronization of Boolean control networks,” IEEE Trans. Neural Netw. Learning Syst., vol. 27, no. 9, pp. 1991–1996, 2016.
194. J. Lu, H. Li, Y. Liu, and F. Li, “Survey on semi-tensor product method with its applications in logical networks and other finite-valued systems,” IET Control Theory and Applications, vol. 11, no. 13, pp. 2040–2047, Aug. 2017.
195. Y. Zhao, B. K. Ghosh and D. Cheng, “Control of large-scale Boolean networks via network aggregation,” IEEE Trans. Neural Netw. Learn. Syst., vol. 27, no. 7, pp. 1527–1536, 2016.
196. M. Anthony, Discrete Mathematics of Neural Networks, Selected Topics. Philadelphia, PA, USA: SIAM, 2001.
197. K. Y. Siu, V. P. Roychowdhury, and T. Kailath, “Depth-size tradeoffs for neural computation”, IEEE Transactions on Computers, vol. 40, no. 12, pp. 1402-1412, 1991.
198. R. Minnick, “Linear-input logic,” IEEE Trans. Electron. Comput., vol. EC-10, pp. 6-16, 1961.