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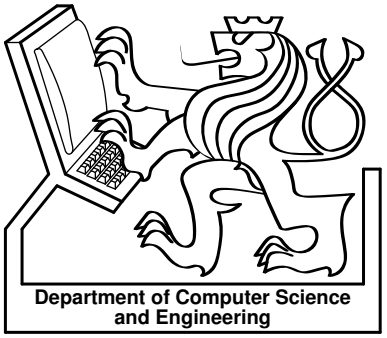

Diploma Thesis

Implementation of DCA Compression Method

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Prohlášení

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Anotace

Komprese dat metodou antislovníku je nová metoda komprese dat založená na faktu, že některé posloupnosti znaků se v textu nikdy nevyskytují. Tato práce se zabývá implementací různých metod DCA (komprese dat metodou antislovníku) založených na pracích Crochemore, Mignosi, Restivo, Navarro a dalších a srovnává výsledky na standardních sadách souborů pro vyhodnocování kompresních metod.

Je představena konstrukce antislovníku pomocí *suffix array* se zaměřením na snížení paměťových nároků statického způsobu komprese. Dále je vysvětlena a implementována dynamická DCA komprese, jsou testována některá možná vylepšení a implementované DCA metody jsou porovnány z hlediska dosaženého kompresního poměru, paměťových nároků a rychlosti komprese a dekomprese. U každé z metod jsou doporučeny vhodné parametry a nakonec jsou shrnuty klady a zápory srovnávaných metod.

Abstract

Data compression using antidictionaries is a novel compression technique based on the fact that some factors never appear in the text. Various DCA (Data Compression using Antidictionaries) method implementations based on works from Crochemore, Mignosi, Restivo, Navarro and others are presented and their performance evaluated on standard sets of files for evaluating compression methods.

Antidictionary construction using *suffix array* is introduced focusing on minimizing memory requirements of the static compression scheme. Also dynamic compression scheme is explained and implemented. Some possible improvements are tested, implemented DCA methods are evaluated in terms of compression ratio, memory requirements and speed of both compression and decompression. Finally appropriate parameters for each method are suggested. At the end pros and cons of evaluated methods are discussed.

Acknowledgements

I would like to thank my thesis supervisor Ing. Jan Holub, Ph.D., not only for the basic idea of this thesis, but also for many suggestions and valuable contributions.

I would also like to thank my parents for their support.

Dedication

To my mother.

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Chapter 1

Introduction

1.1 Problem Statement

DCA (Data Compression using Antidictionaries) is a novel data compression method presented by M. Crochemore in [6]. It uses current theories about finite automata and suffix languages to show their abilities for data compression. The method takes advantage of words that do not occur as factors in the text, i.e. that are forbidden. Thanks to existence of these forbidden words, some symbols in the text can be predicted.

The general idea of the method is quite interesting, first input text is analyzed and all forbidden words are found. Using binary alphabet $\Sigma = \{0, 1\}$ symbols whose occurrences can be predicted using the set of forbidden words are erased. DCA is a lossless compression method, which operates on binary streams.

1.2 State of The Art

Currently there are no available implementations of DCA, all were developed for experimental purposes only. Some research is being done on using larger alphabets rather than binary and on using compacted suffix automata (CDAWGs) for antidictionary construction.

1.3 Contribution of the Thesis

In the thesis dynamic compression using DCA is explained and implemented and antidictionary construction using suffix array is introduced focusing on minimizing memory requirements. Several methods based on data compression using antidictionaries idea are implemented — static compression scheme as well as dynamic compression scheme and static compression scheme with support for almost antifactors, that are words, which occur rarely in the input text. Their results compressing files from Canterbury and Calgary

corpus are presented.

1.4 Organization of the Thesis

In Chapter 2 basic definitions and terminology used in the thesis can be found. Chapter 3 describes the way different methods of DCA are working, brings some examples and also some new ideas. Furthermore dynamic compression scheme is described and anti-dictionary construction using suffix array is introduced. Also basics of different stages in static compression scheme are explained. In Chapter 4 possible implementation of different DCA methods are presented along with some ideas of improving their performance or limiting time and memory requirements. Chapter 5 focuses on experiments with different parameters of implemented methods. Their comparison and results on Canterbury and Calgary corpuses could be found here, provided with comments and recommendations to their usage. The last chapter concludes the thesis and suggests some ideas for future research.

Chapter 2

Preliminaries

Definition 2.1 (Lossless data compression)
A *lossless data compression* method is one where compressing a file and decompressing it retrieves data back to its original form without any loss. The decompressed file and the original are identical, lossless compression preserves data integrity.

Definition 2.2 (Lossy data compression)
A *lossy data compression* method is one where compressing a file and then decompressing it retrieves a file that may well be different to the original, but is "close enough" to be useful in some way.

Definition 2.3 (Symmetric compression)
Symmetric compression is a technique that takes about the same amount of time to compress as it does to decompress.

Definition 2.4 (Asymmetric compression)
Asymmetric compression is a technique that takes different time to compress than it does to decompress.

Note 2.1 (Asymmetric compression)
Typically asymmetric compression methods take more time to compress than to decompress. Some asymmetric compression methods take longer time to decompress, which would be suited for backup files that are constantly being compressed and rarely decompressed. But basically faster compression than decompression is what we want for usual compress once, decompress many times behaviour.

Note 2.2 (Canterbury Corpus)
The Canterbury Corpus[15] is a collection of "typical" files for use in the evaluation of lossless compression methods. The Canterbury Corpus consists of 11 files, shown in Table 2.1. Previously, compression software was tested using a small subset of one or two "non-standard" files. This was a possible source of bias to experiments, as the data used may have caused the programs to exhibit anomalous behaviour. Running

File	Category	Size
alice29.txt	English text	152089
asyoulik.txt	Shakespeare	125179
cp.html	HTML source	24603
fields.c	C source	11150
grammar.lsp	LISP source	3721
kennedy.xls	Excel spreadsheet	1029744
lcet10.txt	Technical writing	426754
plrabn12.txt	Poetry	481861
ptt5	CCITT test set	513216
sum	SPARC Executable	38240
xargs.1	GNU manual page	4227

Table 2.1: Files in the Canterbury Corpus

compression software experiments using the same carefully selected set of files gives us a good evaluation and comparison with other methods.

Note 2.3 (Calgary Corpus)
The Calgary Corpus[4] is the most referenced corpus in the data compression field especially for text compression and is the de facto standard for lossless compression evaluation. It was founded in 1987. It is a predecessor of the Canterbury Corpus.

Definition 2.5 (Compression ratio)
Compression ratio is an indicator evaluating compression performance. It is defined as

$$Compression\ ratio = \frac{Length\ of\ compressed\ data}{Length\ of\ original\ data}.$$

Definition 2.6 (Alphabet)
An *alphabet* Σ is a finite non-empty set of *symbols*.

Definition 2.7 (Complement of symbol)
A *complement* of symbol a over Σ, where $a \in \Sigma$, is a set $\Sigma \setminus \{a\}$ and is denoted $\bar{a}$.

Definition 2.8 (String)
A *string* over Σ is any sequence of symbols from Σ.

Definition 2.9 (Set of all strings)
The *set of all strings* over Σ is denoted Σ^*.

Definition 2.10 (Substring)
String x is a *substring* (*factor*) of string y, if $y = uxv$, where $x, y, u, v \in \Sigma^*$.

Definition 2.11 (Prefix)
String x is a *prefix* of string y, if $y = xv$, where $x, y, v \in \Sigma^*$.

Definition 2.12 (Suffix)
String x is a *suffix* of string y, if $y = ux$, where $x, y, u \in \Sigma^*$.

Definition 2.13 (Proper prefix, factor, suffix)
A prefix, factor and suffix of a string u is said to be *proper* if it is not u.

Definition 2.14 (Length of string)
The *length of string* w is the number of symbols in string $w \in \Sigma^*$ and is denoted $|w|$.

Definition 2.15 (Empty string)
An *empty string* is a string of length 0 and is denoted ε.

Definition 2.16 (Deterministic finite automaton)
A *deterministic finite automaton* (DFA) is quintuple $(Q, \Sigma, \delta, q_0, F)$, where Q is a finite set of states, Σ is a finite input alphabet, δ is a mapping $Q \times \Sigma \to Q$, $q_0 \in Q$ is an initial state, $F \subset Q$ is the set of final states.

Definition 2.17 (Transducer finite state machine)
A *transducer finite state machine* is sixtuple $(Q, \Sigma, \Gamma, \delta, q_0, \omega)$, where Q is a finite set of states, Σ is a finite input alphabet, Γ is a finite output alphabet, δ is a mapping $Q \times \Sigma \to Q$, $q_0 \in Q$ is an initial state, ω is an output function $Q \times (\Sigma \cup \{\varepsilon\}) \to \Gamma$.

Definition 2.18 (Suffix trie [18])
Let $T = t_1 t_2 \cdots t_n$ be a string over an alphabet Σ. String x is a substring of T. Each string $T_i = t_i \cdots t_n$ where $1 \leq i \leq n+1$ is a *suffix* of T; in particular, $T_{n+1} = \varepsilon$ is the empty suffix. The set of all suffixes of T is denoted $\sigma(T)$. The *suffix trie* of T is a tree representing $\sigma(T)$.

More formally, we denote the suffix trie of T as $STrie(T) = (Q \cup \{\perp\}, \Sigma, root, F, g, f)$ and define such a trie as an augmented deterministic finite-state automaton which has a tree-shaped transition graph representing the trie for $\sigma(T)$ and which is augmented with the so called suffix function f and auxiliary state $\perp$. The set Q of the states of $STrie(T)$ can be put in a one-to-one correspondence with the substrings of T. We denote by $\hat{x}$ the state that corresponds to a substring x.

The initial state *root* node corresponds to the empty string ε, and the set F of the final states corresponds to $\sigma(T)$. The transition function g is defined as $g(\hat{x}, a) = \hat{y}$ for all $\hat{x}, \hat{y}$ in Q such that $y = xa$, where $a \in \Sigma$.

The *suffix function* f is defined for each state $\hat{x} \in Q$ as follows. Let $\hat{x} \neq root$. Then $x = ay$ for some $a \in \Sigma$, and we set $f(\hat{x}) = \hat{y}$. Moreover, $f(root) = \perp$.

Automaton $STrie(T)$ is identical to the *Aho-Corasick* string matching automaton [1] for the key-word set $\{T_i \mid 1 \leq i \leq n+1\}$ (*suffix links* are called in [1] *failure transitions*.)

Definition 2.19 (Suffix trie depth)
Suffix trie depth k is the maximum height allowed for the trie. We will denote it as *maxdepth* k.

Note 2.4 (Suffix trie depth limit)
Due to the *suffix trie depth limit* k, suffix trie represents only suffixes $S \subset \sigma(T), \forall x \in S : |x| \leq k$.

Theorem 2.1 (Suffix trie [18])
Suffix trie $STrie(T)$ can be constructed in time proportional to the size of $STrie(T)$ which, in the worst case, is $\mathcal{O}(|T|^2)$.

Definition 2.20 (Suffix tree [18])
Suffix tree $STree(T)$ of T is a data structure that represents $STrie(T)$ in space linear in the length $|T|$ of T. This is achieved by representing only a subset $Q' \cup \{\perp\}$ of the states of $STrie(T)$. We call the states in $Q' \cup \{\perp\}$ the *explicit states*. Set Q' consists of all branching states (states from which there are at least two transitions) and all leaves (states from which there are no transitions) of $STrie(T)$. By definition, *root* is included into the branching states. The other states of $STrie(T)$ (the states other than *root* and $\perp$ from which there is exactly one transition) are called *implicit states* as states of $STree(T)$; they are not explicitly present in $STree(T)$.

Note 2.5 (Suffix link)
Suffix link is a key feature for linear-time construction of the suffix tree. In a complete suffix tree, all internal non-root nodes have a suffix link to another internal node. Suffix link corresponds to function $f(r)$ of state r. If the path from the *root* to a node spells the string bv, where $b \in \Sigma$ is a symbol and v is a string (possibly empty), it has a suffix link to the internal node representing v.

Note 2.6 (Suffix tree)
Suffix tree represents all suffixes of a given string. It is designed for fast substring searching, each node represents a substring, which is determined by the path to the node. The difference between suffix tree and suffix trie could be more obvious from Figure 2.1.

The large amount of information in each edge and node makes the suffix tree very expensive, consuming about ten to twenty times [11] the memory size of the source text in good implementations. The suffix array reduces this requirement to a factor of four, and researchers have continued to find smaller indexing structures.

Definition 2.21 (Antifactor [3])
Antifactor (or *Forbidden Word*) is a word that never appears in a given text.

Let Σ be a finite alphabet and Σ^* the set of finite words of symbols from Σ, the empty word ε included.

Let $L \subset \Sigma^*$ be a factorial language, i.e. $\forall u, v \in \Sigma^*, uv \in L \Rightarrow u, v \in L$. The complement $\Sigma^* \setminus L$ of L is a (two sided) ideal of Σ^*. Denote by $MF(L)$ its *base*: $\Sigma^* \setminus L = \Sigma^* MF(L) \Sigma^*$.

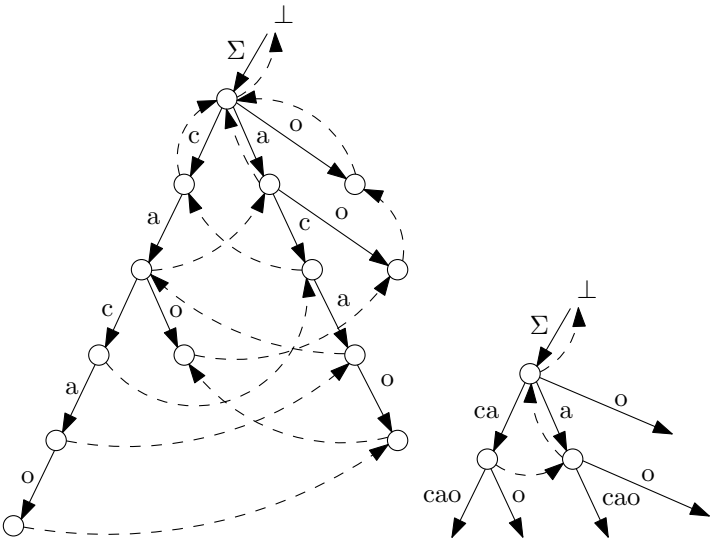

Figure 2.1: Comparison of suffix trie (left) and suffix tree over string "cacao"

$MF(L)$ is the set of Minimal Forbidden words for L. A word $v \in \Sigma^*$ is *forbidden* for L if $v \notin L$. The forbidden word is *minimal* if it has no proper factors that are forbidden.

Definition 2.22
The set of all minimal forbidden words we call *an antidictionary AD*.

Definition 2.23 (Internal nodes)
The *internal nodes* of the suffix trie correspond to nodes actually represented in the trie, that is, to factors of the text.

Definition 2.24 (External nodes)
The *external nodes* correspond to antifactors, and they are implicitly represented in the tree by the null pointers that are children of internal nodes. The exception are the (forcedly) external nodes at depth $k + 1$, that are children of internal nodes at the maximum depth k, which may or may not be antifactors.

Definition 2.25 (Terminal nodes)
Each external node of the trie that surely corresponds to an antifactor (i.e. at *depth* $< k$) is converted into an internal (leaf) node. These new internal nodes are called *terminal nodes*.

Note 2.7 (Terminal nodes)
Note that not all leaves are *terminal*, as some leaves at depth k are not antifactors.

Definition 2.26 (Almost antifactor [7])
Let us assume that a given string s appears m times in the text, and that $s.0$ and $s.1$,

where '.' means concatenation[1], appear m_0 and m_1 times, respectively, so that $m = m_0 + m_1$ (except if s is at the end of the text, where $m = m_0 + m_1 + 1$). Let us assume that we need e bits to code an exception. Hence, if $m > e * m_0$, then we improve the compression by considering $s.0$ as an antifactor (similarly with $s.1$). *Almost antifactors* are string factors, that improve compression when considered as antifactors.

Definition 2.27 (Suffix array)
Suffix array is a sorted list of all suffixes of given text represented by pointers.

Note 2.8 (Suffix array [12])
When a suffix array is coupled with information about the *longest common prefixes* (*lcps*) of adjacent elements in the suffix array, string searches can be answered in $\mathcal{O}(P + \log N)$ time with a simple augmentation to a classic binary search, P is searched string length. The suffix array and associated lcp information occupy a mere 2N integers, and searches are shown to require at most $P + \lceil \log_2 (N-1) \rceil$ single-symbol comparisons.

The main advantage of *suffix arrays* over *suffix trees* is that, in practice, they use three to five times less space.

Definition 2.28 (Stopping pair [6])
A pair of words (v, v_1) is called *stopping pair* if $v = ua, v_1 = u_1 b \in AD$, with $a, b \in \{0,1\}, a \neq b$, and u is a suffix of u_1.

Lemma 2.1 (Only one stopping pair [6])
Let AD be an antifactorial antidictionary of a text $t \in \Sigma^*$. If there exists a stopping pair (v, v_1) with $v_1 = u_1 b, b \in \{0,1\}$, then u_1 is a suffix of t and does not appear elsewhere in t. Moreover there exists at most one pair of words having these properties.

[1] The concatenation mark '.' is omitted when it is obvious.

Chapter 3

Data Compression Using Antidictionaries

3.1 DCA Fundamentals

DCA (Data Compression using Antidictionaries) is a novel data compression method presented by M. Crochemore in [6]. It uses current theories about finite automata and suffix languages to show their abilities for data compression. The method takes advantage of words that do not occur as factors in the text, i.e. that are forbidden, we call them *forbidden words* or *antifactors*. Thanks to existence of these forbidden words, we can predict some symbols in the text.

Just imagine, that we have an antifactor $w = ub$, where $w, u \in \Sigma^*$, $b \in \Sigma$ and while reading text, we find occurence of string u. Because the next symbol can't be b, we can predict it as $\bar{b}$. Therefore when we compress the text, we erase symbols that can be predicted and in reverse when decompressing we predict the erased symbols back.

The general idea of the method is quite interesting, first we analyze input text and find all antifactors. Using binary alphabet $\Sigma = \{0, 1\}$ we erase symbols, whose occurrences can be predicted using the set of antifactors. As we can see, DCA is a lossless compression method, which operates on binary streams so far, i.e. it is working with single bits, not symbols of larger alphabets, but some current research is dealing with this, too.

Example 3.1
Compress string $s = u.1, s \in \Sigma^*$, using antifactor $u.0$.

Because $u.0$ is an antifactor, the next symbol after u must be 1. So we can erase the symbol 1 after u.

To be able to compress the text, we need to know the forbidden words. First we analyze the input text and find all antifactors, which can be used for text compression (Figure 3.1). For our purpose, we don't need all antifactors, but just the minimal ones. The antifactor

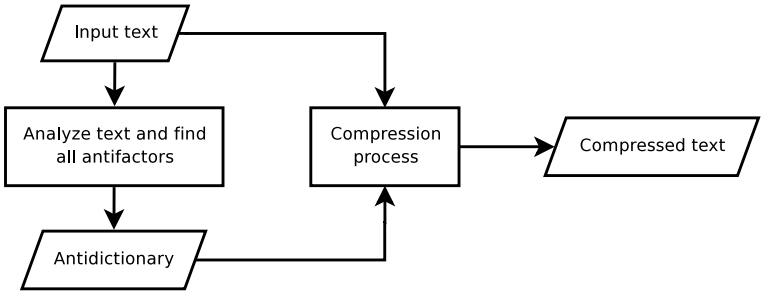

Figure 3.1: DCA compression basic scheme

is *minimal* when it does not have any proper factor, that is forbidden. The set of all minimal antifactors — the *antidictionary* AD is sufficient, because for every antifactor $w = uv$, where u is a string over Σ, there exists a minimal antifactor v in antidictionary AD.

Currently there is not any known good working implementation of the DCA compression method. Yet we are trying to develop it, we are still far from practical use, due to the excessive system resources needed to compress even a small file. However thanks to rapid research progress of strings, suffix arrays, suffix automata (DAWGs), compacted suffix automata (CDAWGs) and other related issues, we might be able to design a practical implementation soon.

3.2 Data Compression and Decompression

Let w be a text on the binary alphabet $\{0, 1\}$ and let AD be an antidictionary for w [6]. By reading the text w from left to right, if at a certain moment the current prefix v of the text admits as suffix a word u' such that $u = u'x \in AD$ with $x \in \{0, 1\}$, i.e. u is forbidden, then surely the symbol following v in the text cannot be x and, since the alphabet is binary, it is the symbol $y = \bar{x}$. In other terms, we know in advance the next symbol y, that turns out to be redundant or predictable.

The main idea of this method is to eliminate redundant symbols in order to achieve compression. The decoding algorithm recovers the text w by predicting the symbol following the current prefix v of w already decompressed.

Example 3.2
Compress text 01110101 using antidictionary $AD = \{00, 0110, 1011, 1111\}$:

```
step:   1  2   3    4     5      6       7        8
input:  0  01  011  0111  01110  011101  0111010  01110101
        |  |.  |./  |./.  |./..  |./...  |./....  |./.....
output: 0  0   01   01    01     01      01       01
```

1. Current prefix: ε. There is no such word x in AD, so we pull 0 from input and push

it to output.

2. Current prefix: 0. There is word 00 in AD, so we erase the next symbol (1).
3. Current prefix: 01. There is no such word $u = u'x$ in AD, where u is suffix of 01. We read 1 from input and push it to output.
4. Current prefix: 011. There is word 0110 in AD, so we erase the next symbol (1).
5. Current prefix: 0111. There is word 1111 in AD, so we erase the next symbol (0).
   ⋮

The result of compressing text 01110101 is 01. To be able to decompress this text, we need to store the antidictionary and the original text length also, which could be more obvious from the following decompression example.

Example 3.3
Decompress text 01 using antidictionary $AD = \{00, 0110, 1011, 1111\}$.

Decompression is just an inversed compression algorithm:

1. Current prefix: ε. There is no such word x in AD, so we pull 0 from input and push it to output.
2. Current prefix: 0. There is word 00 in AD, so we predict the next symbol as 1 and push it to output.
3. Current prefix: 01. There is no such word $u = u'x$ in AD, where u is suffix of 01. We read 1 from input and push it to output.
4. Current prefix: 011. There is word 0110 in AD, so we predict the next symbol as 1 and push it to output.
5. Current prefix: 0111. There is word 1111 in AD, so we predict the next symbol 0 and push it to output.
   ⋮

```
step:   1  2   3    4     5      6       7        8
input:  0  0   01   01    01     01      01       01
        |  |   | \  | \   | \    | \     | \      | \
output: 0  01  011  0111  01110  011101  0111010  01110101
```

After decompression of text 01 we get the original text 01110101. What is important is that we don't know exactly when to stop the algorithm by knowing just the compressed text and the antidictionary. This means we need to know the length of the original text or we could decompress even infinitely. Another possibility is to store the number of erased

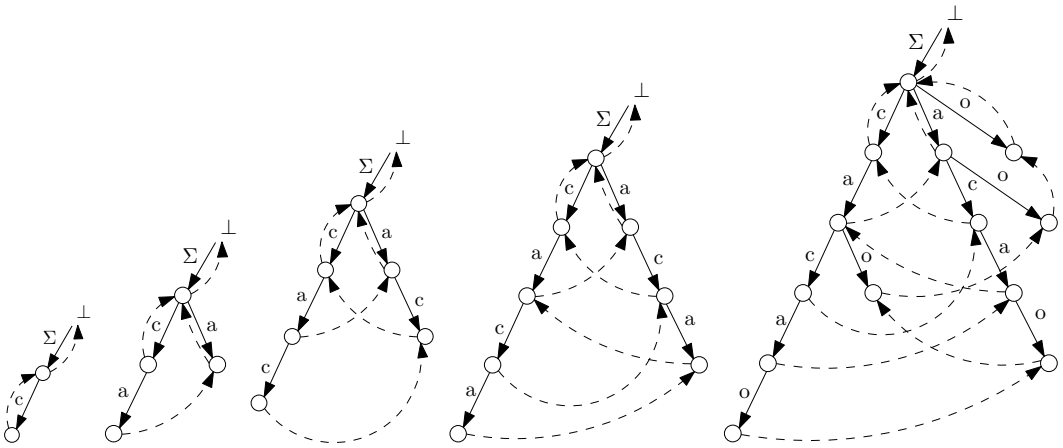

Figure 3.2: Constructing suffix trie for text "cacao"

symbols after using the last input bit, which could be sufficient for most implementations, but this supposes that we can determine exactly end of the input text.

For compression and decompression process, the antidictionary must be able to answer the query on a word v, if there exists a word $u = u'x, x \in \{0,1\}, u \in AD$ such, that u' is a suffix of v. The answer determines, if the symbol x will be kept or erased in the compressed text. To speedup the queries, we can represent the antidictionary as a finite transducer, which leads to fast linear-time compression and decompression. Then we can compare it to the fastest compression methods. To build the compression/decompression transducer, we need a special compiler, that builds the antidictionary first, and then constructs the automaton over it.

3.3 Antidictionary Construction Using Suffix Trie

As it turns out later, the most complex task of the DCA method is just the antidictionary construction. It's natural to use suffix trie structure for collecting all factors of the given text, although any other data structure for storing factors of words can be used, such as suffix trees, suffix automata (DAWGs), compacted suffix automata (CDAWGs), suffix arrays, ...

Let's consider text $t = c_1c_2c_3 \dots c_n$ of length n, where c_i is a symbol at position i. We are adding words $c_1, c_1c_2, c_1c_2c_3, \dots, c_1c_2c_3 \dots c_n$ step by step. Because we are adding the words to a suffix trie structure representing all suffixes of the given words, we get all factors of text t. See Figure 3.2 for example of constructing suffix trie for text "cacao".

To construct an antidictionary from the suffix trie, we add all antifactors of the text. For every factor $u = u'x$, we add an antifactor $v = u'y, x \neq y$, if factor v doesn't already exist. The resulting antidictionary won't be minimal so we need to select only the minimal antifactors. The antifactor v is minimal when there does not already exist an antifactor

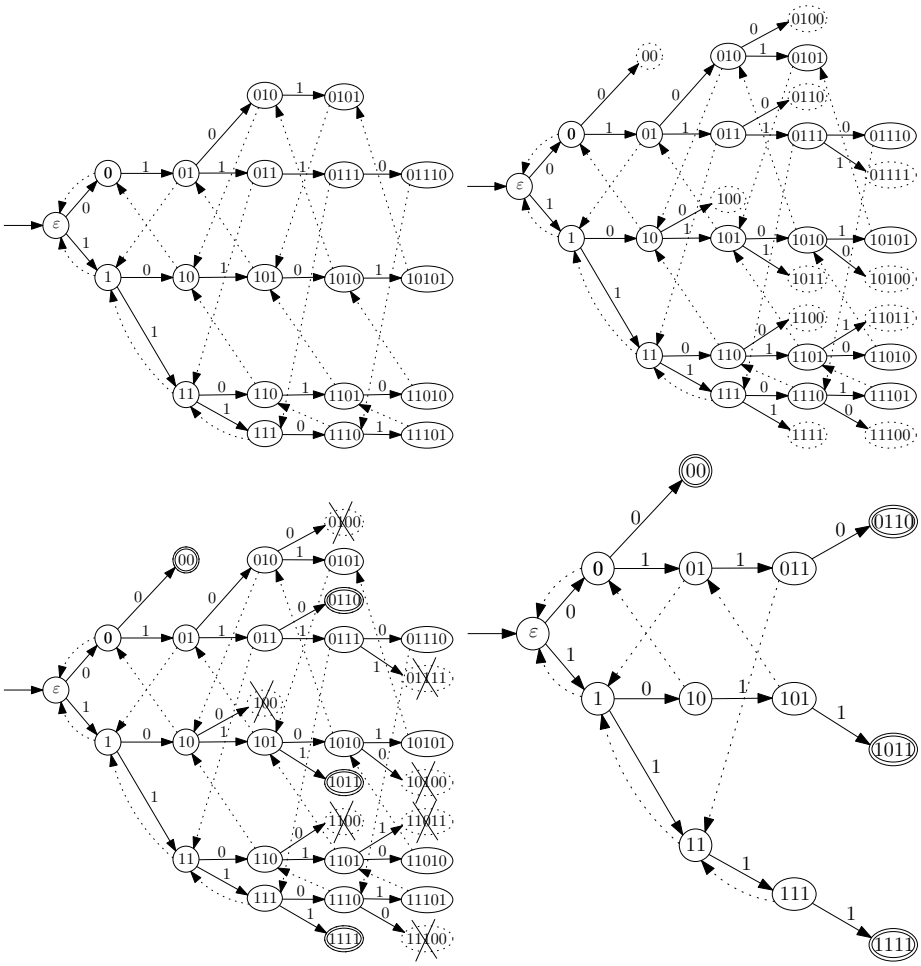

Figure 3.3: Antidictionary construction over text "01110101" using suffix trie

w such that $v = v'w$, i.e. there is no such antifactor w, that is a suffix of v. This can be easily checked using suffix link (dashed line in Figure 3.2). The antifactor $v = u'y$ is minimal, when $f(u')y$ is an internal node, otherwise a shorter antifactor w certainly exists.

Example 3.4
Build an antidictionary for text "01110101" with maximal trie depth $k = 5$.

We construct a suffix trie over the text, then we add all antifactors. Antifactors together form a set $\{00, 100, 0100, 0110, 1011, 1100, 1111, 01111, 11100, 11011, 10100\}$, which is obviously not antidictionary (set of minimal antifactors), e.g. 00 is a suffix of antifactors $100, 0100, 1100, 11100, 10100$. We have to remove antifactors, that are not minimal. Resulting set is antidictionary $AD = \{00, 0110, 1011, 1111\}$. See Figure 3.3 for suffix trie construction process. On the final diagram we can see trie containing only necessary nodes to represent the antidictionary, leaf nodes are antifactors.

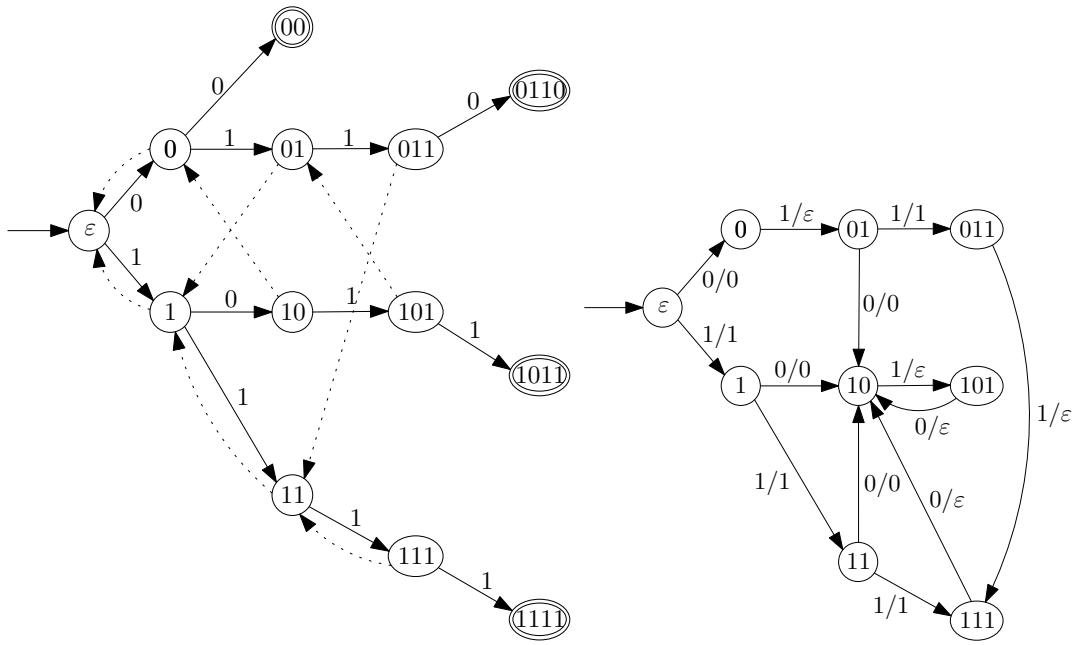

Figure 3.4: Antidictionary $AD = \{00, 0110, 1011, 1111\}$ and the corresponding compression/decompression transducer

For representing the antidictionary we don't need the whole tree, so we keep only the nodes and links, which lead to antifactors. This simplified suffix trie is going to be used later for compression/decompression transducer building.

3.4 Compression/Decompression Transducer

As we have suffix trie of the antidictionary now, which is in fact an automaton accepting antifactors, we are able to construct a compression/decompression transducer from it. From every node r except terminal nodes we have to make sure that transitions for both 0/1 symbols are defined. For a missing transition $\delta(r, x), x \in \{0, 1\}$, we create this transition as $\delta(f(r), x)$. As we do this in breadth-first search order, $\delta(f(r), x)$ is always defined. The only exception is the root node, which needs special handling. Transducer construction can be found in more detail in [6] as "L-automaton".

Then we remove the terminal states and assign output symbols to the edges. The output sybols are computed as follows: if a state has two outgoing edges, output symbol is the same as the input one; if a state has only one outgoing edge, output symbol is an empty word (ε). An example is presented in Figure 3.4.

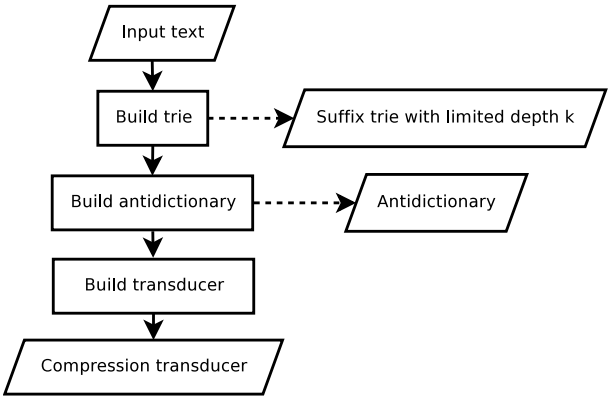

Figure 3.5: Basic antidictionary construction

3.5 Static Compression Scheme

Antidictionary is needed to build the compression/decompression transducer, but in practical applications the antidictionary is not apriori given, we need to derive it from the input text or from some "similar data source". We build the antidictionary using one of the techniques mentioned in Section 3.3. With bigger antidictionary we could obtain better compression, but it grows with the length of input text and we need to control its size, or its representation will be inefficient and the compression could be very slow. A rough solution is to limit length of the words belonging into antidictionary, which is done by limiting suffix trie depth during its construction. This will simplify and lower the system requirements for building the antidictionary. This simple antidictionary construction scheme is presented in Figure 3.5.

3.5.1 Simple pruning

In static compression scheme we compress and decompress the data with the same antidictionary. However the decompression process has to know the original antidictionary, that was used for compression. That's why we need to store the used antidictionary together with the compressed data. The question is, if the stored antiword will erase more bits, than the bits needed to actually store the antiword. Possible antidictionary representations will be discussed in Section 4.5.

Let's consider that we know, how many bits are needed for representation of each antiword, then we can compute the gain of each antiword and prune all antiwords with negative gain. We call this *simple pruning*. After applying this function on the antidictionary, we can improve the compression ratio of the static compression scheme by storing only the "good" antiwords and using just them for compression. Our static compression scheme will now look like Figure 3.6.

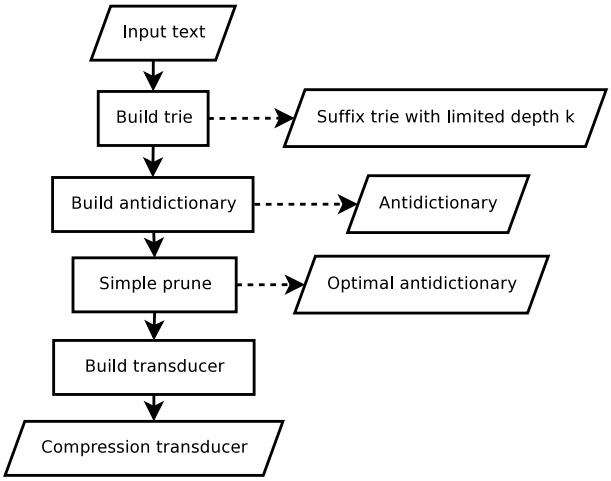

Figure 3.6: Antidictionary construction using simple pruning

3.5.2 Antidictionary self-compression

As with static approach we need to store the antidictionary together with the compressed data, it might cross our minds, that there is a possibility to compress also the antidictionary itself. This depends heavily in which form we are going to represent the antidictionary list. Basically we have two options:

1. *antiword list* – antidictionary size, length of each antiword and the antiword itself. With this we could use all previous antiwords to compress/decompress the following antiwords, e.g. for $AD = \{00, 0110, 1011, 1110\}$ we get $AD' = \{00, 010, 101, 1110\}$.

2. *antiword trie* – trie structure represented in some suitable way. Using this method we are actually saving a binary tree, of course the tree can be also self-compressed. Longer antiwords can be compressed using shorter antiwords, but with some limitations.

   Let's consider the following, $w = ubv$ is an antiword, $u, v \in \Sigma^*, b \in \Sigma$. If we compressed antiword $w = ubv$ using antiword $z = u\bar{b}$, it would become $w' = uv$ and $|w'| = |z|$ could happen, which means, that nodes representing antiwords z and w' would be on the same level in the compressed suffix trie and could overlap. This is generally not what we want, because we wouldn't be able to reconstruct the original tree. Reasonable solution is to erase symbol b from antiword $w = ubv$ if and only if there exists antiword $y = x\bar{b}$, where x is a proper suffix of u, which makes sure, that $|w'| > |y|$.

Example 3.5
Self-compress trie of the antidictionary $AD = \{00, 0110, 1011, 1110\}$:

Only 1011 antiword path can be compressed, we remove node 101 as it can be predicted due to antiword 00 and connect nodes 10 and 1011. Antiword 1011 will actually become

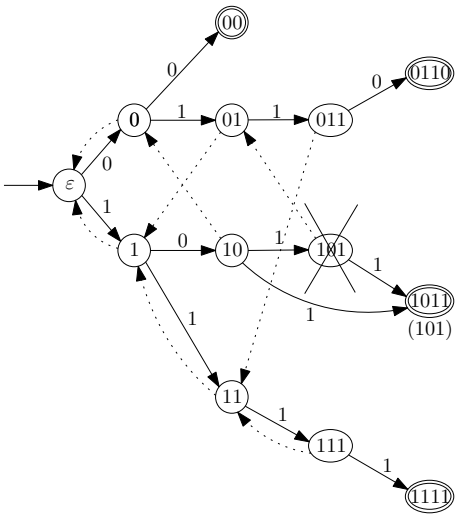

Figure 3.7: Self-compression example

101 in the new representation. Antiword 0110 cannot be compressed, because compressing 01 to just 0 will lead to a nondeterministic antidictionary reconstruction. See Figure 3.7. Self-compression algorithm will be explained thoroughly in Section 4.4.4.

With antidictionary self-compression we can further improve our static compression scheme. And what about combining this technique with simple pruning? In fact it makes things a bit harder, because self-compressing changes the antidictionary representation and influences antiword gains. For better precision we do simple pruning on a self-compressed tree and after pruning we self-compress the antidictionary and consider it as final.

However this simplification isn't accurate, after self-compressing the trie still may not be optimal, because on the other side simple pruning affects self-compression. We can fix this by applying simple pruning and self-compressing iteratively as long as some nodes are pruned from the trie. Both single and multiple self-compression/simple prune rounds are demonstrated in Figure 3.8.

3.6 Antidictionary Construction Using Suffix Array

In previous sections we used suffix trie for antidictionary construction. One of the main problems of suffix trie structure is its memory consumption, the large amount of information in each edge and node make it very expensive. Even for depth k larger than 30 and small input files, suffix trie size grows very fast and needs tens to hundreds Megabytes of memory. Also creation and traversal through the whole trie is quite slow.

We can consider other methods for collecting all text factors. As we are dealing with

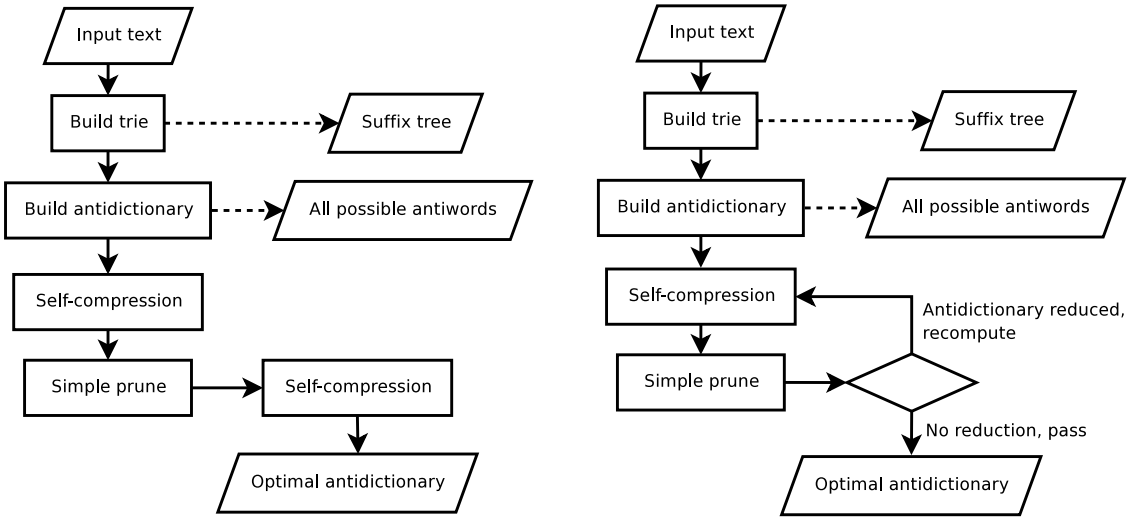

Figure 3.8: Antidictionary construction using single (a) and multiple (b) self-compression/simple prune rounds

binary alphabet, this limits usage of some of them — suffix trees, DAWGs or CDAWGs, which are designed mainly for larger alphabets. Also antidictionary constructing algorithms need to be modified fundamentally and an appropriate way for efficiently representing these structures has to be developed. This work focuses on usage of suffix arrays, which were a favourite subject to study in recent years and many implementations are already available.

3.6.1 Suffix array

The suffix trees were originally developed for searching for suffixes in the text. Later the suffix arrays were discovered. They are used for example in Burrows-Wheeler Transformation [5] and *bzip2* compression method. The suffix array is a sufficient replacement for the suffix trees allowing some tasks that were done with suffix trees before. The major advantage is much smaller memory requirements and also smaller complexity considering some tasks performed during DCA compression, e.g. node visits counting. It is possible to save even more space using compressed suffix arrays [9].

The *suffix array* is built on top of the input text, representing all text suffixes and alphabetically sorted. In fact it contains indexes pointing into the original text. Because for most algorithms, this is not enough, we also build *lcp* array on top of the input text and suffix array. An example of suffix array can be seen in Table 3.1. Symbol # denotes the end of the text, lexicographically the smallest symbol.

Lcp (Least Common Prefix) array contains the adjacent word prefix length common with the previous word. With just these two structures we can do all needed operations, as we will show later. String searches can be answered with a complexity similar to the binary

i	0	1	2	3	4	5	6
t_i	a	b	c	a	a	b	#
SA	6	3	4	0	5	1	2
LCP	0	0	1	2	0	1	0
	#	a	a	a	b	b	c
		a	b	b	#	c	a
		b	#	c		a	a
		#		a		a	b
				a		b	#
				b		#	
				#			

Table 3.1: Suffix array for text "abcaab"

search, a memory representation requires two arrays of pointers, one for suffix array and one for lcps, their sizes are equivalent to the length of input text.

Let's suppose we have an efficient algorithm for suffix array and lcp construction. What we need to realize for antidictionary construction is, that we are constructing suffix array over the binary alphabet, so the suffix array and lcp length will be 8 times length of the input text. Still memory requirements for suffix array construction depends only on the length of input text with $\mathcal{O}(N)$, instead of suffix trie almost exponential complexity, depending on the trie depth.

3.6.2 Antidictionary construction

The suffix arrays offer text searching capabilities similar to suffix tries, thus why not to use them for antidictionary construction. First mention of this idea can be found in [19]. Now antidictionary construction using suffix array with asymptotic complexity $\mathcal{O}(k * N \log N)$ will be explained, k is maximal antiword length. The process takes two adjacent strings at a time and finds antifactors. Special handling is needed for the last item, which is not in pair.

1. Take two adjacent strings u_i and u_{i+1} from suffix array, $u_i, u_{i+1} \in \Sigma^*$.
2. Skip their common prefix c utilizing LCP, $u_i = cxv, u_{i+1} = cyw, x \neq y$ and test the first differing symbol, $c, v, w \in \Sigma^*$, $x, y \in \Sigma$. If $x = \#, y = 1$, then add antifactor $c.0$.
3. For each symbol v_j of string $u_i = cxv$ such, that $v_j = 0$, add antifactor $cxv_1 \dots v_{j-1}1$.
4. For each symbol w_j of string $u_{i+1} = cyw$ such, that $v_j = 1$, add antifactor $cyw_1 \dots w_{j-1}0$.
5. Repeat previous steps for all suffix array items.

i	0	1	2	3	4	5	6	7	8
t_i	0	1	1	1	0	1	0	1	#
SA	8	6	4	0	7	5	3	2	1
LCP	0	0	2	2	0	1	3	1	2
	#	0	0	0	1	1	1	1	1
		$\boxed{\underline{1}}$	1	1	#	0	0	1	1
		#	0	1		$\boxed{1}$	1	0	1
			$\boxed{1}$	$\boxed{\underline{1}}$		#	$\boxed{\underline{0}}$	$\boxed{1}$	$\boxed{\underline{0}}$
			#	$\boxed{0}$			$\boxed{1}$	$\boxed{0}$	$\boxed{1}$

Table 3.2: Suffix array for binary text "01110101" highlighting antifactor positions

6. For the last item $u_n = v$, for each symbol $v_j = 0$, add antifactor $v_1 \dots v_{j-1}1$.

This simple algorithm finds all text antifactors, we only need to limit antifactor length. Using this technique we find all antifactors, but what we really want are minimal antifactors. One possible way is to construct a suffix trie from the found antifactors and then choose just the minimal antifactors using suffix links. Second option is to utilize the suffix array ability for searching strings.

To check if antifactor $u = av, a \in \{0, 1\}$ is minimal, try to find string v in the suffix array. If string v appears in the text, then the antifactor u is minimal. Search for a string in suffix array equipped with lcp array takes $\mathcal{O}(P + \log N)$ time, where P is length of v.

Example 3.6
Build antidictionary for text "01110101" using suffix array.

First we build suffix array and lcp structure, it can be seen in the Table 3.2, suffix tree for the same text can be found in Figure 3.3. Using algorithm introduced above we find possible antifactors, their positions are marked with a frame around symbols. Positions with minimal antifactors are underlined. This leads to the set of minimal antifactors, antidictionary $AD = \{00, 0110, 1011, 1111\}$, which corresponds with antidictionary computed using suffix trie.

3.7 Almost Antifactors

The idea of almost antifactors was introduced in [7]. After more detailed examination of antidictionaries we can discover also their odd behaviour. If we try to compress the string 10^{n-1} with $k \geq 2$, then the result is satisfying because we can use $\{01, 11\}$ as our antidictionary. This permits compressing the string to $(1, n)$ plus the small antidictionary. However, if we reverse the string to $0^{n-1}1$, then for any $k < n$ the set of antifactors contains {10, 11}, which indeed does not yield any compression. The classical algorithm produces an empty antidictionary. Yet, both strings have the same 0-order entropy.

As we can see, the main problem is that a single occurrence of a string in the text (in our second example the string "01") outrules it as an antifactor. In a less extreme case, it may be possible that a string $sb, s \in \Sigma^*, b \in \Sigma$ appears just a few times in the text, but its prefix s appears so many times, that it is better to consider sb as an antifactor. Of course, to be able to recover the original text, we need to code somehow those text positions where the bit predicted by taking the string as an antifactor is wrong. We call *exceptions* the positions in the original text where this happens, that is, the final positions of the occurrences of sb in the text.

3.7.1 Compression ratio improvement

Usage of almost antifactors can theoretically bring compression ratio improvement to original DCA algorithm, but it's not so easy, as it looks at the first sight. By introducing some almost antifactors we can remove also "good" antifactors, whose gain was better than of the newly introduced almost antiword. Also we completely prune branches connected to factors we turned into antifactors. In contrast of improving gain, introducing new almost antiwords we lose some gain elsewhere, the whole tree changes a lot.

The key problem [7] is that the decision of what is an almost antifactor depends in turn on the gains produced, so we cannot separate the process of creating the almost antifactors and computing their gains: creating an almost antifactor changes the gains upwards in the tree, as well as the gains downwards via suffix links. So there seems to be no suitable traversal order. It is not possible either to do a first pass computing gains and then a second pass deciding which will be terminals, because if one converts a node into terminal its gain changes and modifies those of all the ancestors in the tree. It is not possible to leave the removal of redundant terminals for later because the removal can also change previous decisions on ancestors of the removed node.

3.7.2 Choosing nodes to convert

In the original document two ways of solving this problem were introduced, one-pass and multi-pass heuristics. Both heuristics work with the whole suffix trie, not with just the trie with antifactors. This is very limiting for designing a fast DCA implementation, multi-pass heuristics needs repetitious tree traversal over the whole suffix trie, which is very expensive.

Although we can use the one-pass heuristics, according to [7] it doesn't perform as well as the multi-pass one. The one-pass heuristics first makes breadth-first top-down traversal determining which nodes will be terminal, and then applies the normal bottom-up optimization algorithm to compute gains and decide which nodes deserve belonging to the antidictionary.

The problem of heuristics is that it's not accurate, since considering that it may be a bad decision to convert into terminal a node that turns out to have a subtree with a large gain, we lose it, an also when we give the preference to the highest node, it is not necessarily always the best choice. Even when testing one-pass heuristics with deeper

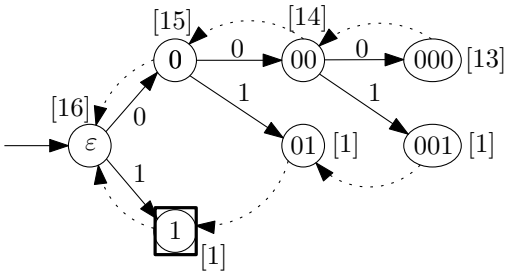

Figure 3.9: Example of using almost antiwords

Node	Gain as an antiword
0	$16 - 5 * 15 = 59$
1	$16 - 5 * 1 = 11$
00	$15 - 5 * 14 = -55$
01	$15 - 5 * 1 = 10$
000	$14 - 5 * 13 = -51$
001	$14 - 5 * 1 = 9$

Table 3.3: Example of node gains as antiwords

suffix tries, we can get worse results than with the classical approach, it depends on the particular file. Using multi-pass heuristics, $k/2$ passes count are recommended for good results, but it is not suitable for us because of its time complexity.

Example 3.7
Compress text $0000000000000001 = 0^{15}1$ using suffix trie depth limit $k = 3$ with classical approach and with almost antiwords, then compare the results.

We build suffix trie from the text, as can be seen in Figure 3.9. Next to each node there is a visit count written in brackets. Let's suppose the following: representation of every node in antidictionary trie takes $A = 2$ bits + 2 extra bits for coding root node, representation of each exception takes $E = 5$ bits. Now we can compute gain of each node r as an antiword using function $g(r)$, $p(r)$ is parent of r, $v(r)$ is visit count of r,

$$g(r) = v(p(r)) - E * v(r).$$

After gain computation (see Table 3.3) we convert node 1 to a terminal node because of its positive gain. Nodes 01 and 001 are not converted, because they would be not minimal antifactors. We obtain antidictionary $AD = \{1\}$, which compresses the input data to ε.

Using classical approach we get an empty dictionary, which means no compression at all. Our output will look like

$$len_{classical} = empty\ AD(2b) + original\ length(5b) + data(16b) = 23b.$$

Using almost antiword approach we get the antidictionary with one word, one exception

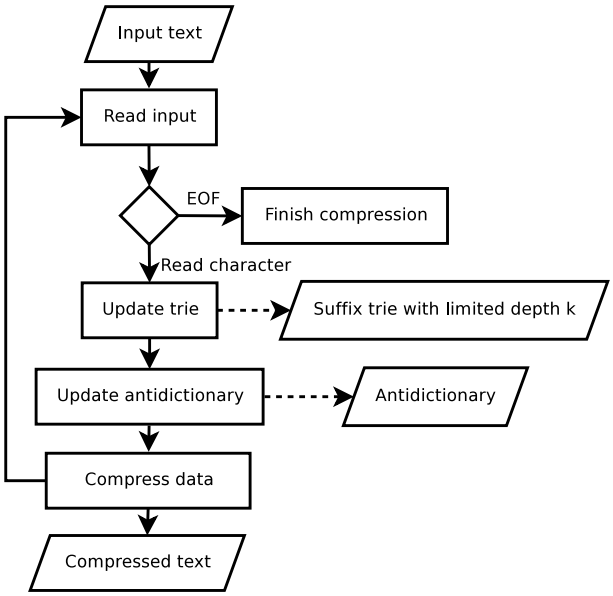

Figure 3.10: Dynamic compression scheme

and empty compressed data, our output size will be

$$len_{almost\text{-}aw} = AD(2b + 2b) + original\ length(5b) + data(0b) + exception(1 * 5b) = 14b.$$

As we can see, using almost antiword improvement we saved 9 bits in comparison with classical approach and this could be even more interesting for longer texts.

3.8 Dynamic Compression Scheme

Till now we were considering static compression model, where the whole text must be read twice, once when the antidictionary is computed and once when we are actually compressing the input. Using this method we need to store the antidictionary separately. To do it in an efficient way, we use techniques like simple pruning and self-compression.

But there is also another possible solution how to use DCA algorithm. With dynamic approach we read text only once, we compress input and modify antidictionary at the same time. Whenever we read some input, we recompute the antidictionary again and use it for compressing the next input (Figure 3.10). The compression process can be described in these steps:

1. Begin with an empty antidictionary.
2. Read input and compress it using the current antidictionary.
3. Add the read symbol to the factor list and recompute antidictionary.

4. Every exception that occurs, code and save into separate file.

5. Repeat steps until the whole input processed.

Because we don't know the correct antidictionary in advance, we are making mistakes in predicting the text. Every time we read a symbol that violates the current antidictionary and brings a forbidden word, we need to handle this exception. We do it by saving distances between the two adjacent exceptions. This can be represented by number of successful compressions (bits erased) between the exceptions, there is no need to count symbols just passed to the algorithm in non-determined transitions. Exception occurs only when there exists a transition with ε output from the current state, but we don't take it.

Exceptions can be represented by some kind of universal codes, arithmetic or Huffman coding. It needs to be stored along the compressed data in a separate file or when we use output buffers large enough, they can be a direct part of compressed data.

3.8.1 Using suffix trie online construction

For compressing text using the dynamic compression model we don't need a pruned antidictionary or even a set of minimal antifactors, because the compressor and the decompressor share both the same suffix trie, they can use all available antifactors directly. With advantage we can use suffix tries for representing already collected factors as well as for compressing the input online. We use the suffix trie as an automaton, maintaining suffix links. For this we can use the following algorithm:

```
1   Dynamic−Build−Fact (int maxdepth > 0)
2       root ← new state;
3       level(root) ← 0;
4       cur ← root;
5       while not EOF do
6           read(a);
7           p ← cur;
8           if level(p) = maxdepth then
9               p ← fail(p);
10          while p has no child and p ≠ root do
11              p ← fail(p);
12          if p has only one child δ(p, x) then
13              if x = a then
14                  erase symbol a
15              else
16                  write exception;
17          else
18              write a to output;
19          cur ← Next(cur,a,maxdepth);
20      return root;

1   Next (state \textit{cur}, bool a, int maxdepth > 0)
2       if δ(cur, a) defined then
```

```
3            return δ(cur, a)
4        else if level(\textit{cur}) = maxdepth then
5            return Next(fail(\textit{cur}), a, maxdepth)
6        else
7            q ← new state;
8            level(q) ← level(\textit{cur}) + 1;
9            δ(cur, a) ← q;
10           if cur = root then fail(q) = root;
11           else fail(q) ← Next(fail(\textit{cur}),a,maxdepth);
12           return q;
```

Function *Dynamic-Build-Fact*() builds suffix trie and compresses data at once, function *Next*() takes care of creating suffix links and missing nodes up to the root node. For dynamic compression we need to know only $\delta(p, a)$ transitions, *fail* function and current level of the node, where p is some node, $a \in \{0, 1\}$. This is less than half information needed for each node and edge in comparison with suffix trie representation in static approach, which means less memory requirements. Considering time asymptotic complexity of *Dynamic-Build-Fact*() gives us only $\mathcal{O}(N * k)$, which is identical to suffix trie construction complexity in Section 4.4.1, but already compressing text where static compression scheme starts.

Example 3.8
Compress text 11010111 using dynamic compression scheme.

We start compressing from the beginning, but it could be useful to skip some symbols and get the suffix trie filled a bit. It's typical to get many exceptions at the beginning, because the suffix trie is only forming at first. This is subject for further experiments. Suffix trie construction process with antifactors found in every step can be seen in Figure 3.11.

Compression process in steps can be seen in Figure 3.4. We get output: "`0 E 1 . E . E .`", where `C` means compressed, `E` means exception and '`.`' is an empty space after erased symbol. Totally 3 exceptions, 3 compressions occurred and 2 symbols were passed. What we can see, is that antidictionary changes only when we pass a new symbol or when an exception occurs, while the set of all antifactors can change any time.

3.8.2 Comparison with static approach

We can think about advantages of this method: we don't have to separately code the antidictionary, do self-compression or even to simple prune it. We simply use all antifactors found yet. Memory requirements are smaller, method is quite fast, as it does not need to do breadth first search for building antidictionary or any other tree traversal for computing gains. Even it is very simple to implement it if we don't bother with suffix trie memory greediness and we don't need to read the text twice as in the static scheme.

There are some disadvantages, too, decompression will be slower, it makes the method symmetric, because decompression process must do almost the same as compression. As we build antidictionary dynamically, parallel compressors/decompressors are not possible

input	read text	output	antidictionary	all antifactors
0	1	0	1	1
1	01 (E)	except	00	00
1	011	1	00, 10	00, 10, 010
1	0111 (C)		00, 10	00, 10, 010, 110, 0110
0	01110 (E)	except	00, 010, 0110, 1111	00, 010, 0110, 1111, 01111
1	011101 (C)		00, 010, 0110, 1111	00, 010, 100, 0110, 1100, 1111, 01111, 11100
0	0111010 (E)	except	00, 0110, 1011, 1111	00, 100, 0110, 1011, 1100, 1111, 01111, 11011, 11100
1	01110101 (C)		00, 0110, 1011, 1111	00, 100, 0110, 1011, 1100, 1111, 01111, 10100, 11011, 11100

Table 3.4: Dynamic compression example

to use, also we lose one of DCA strong properties — pattern matching in compressed text. Efficient representation of the exceptions is a problem, but can be solved using some universal coding or e.g. Huffman coding and storing the exceptions separately.

With this method, it is possible to reach better compression ratios than with the static compression scheme. These results were presented in the original paper [6]. But as this method is not asymmetric and the decompression has the same complexity as compression, this method is not suitable for compress once, decompress many times behaviour.

3.9 Searching in Compressed Text

Compressed pattern matching is a very interesting topic and many studies have been already made on this problem for several compression methods. They focus on linear time complexity proportional not to the original text length but to the compressed text length. And one of the most interesting properties of text compressed using antidictionaries is just its ability of pattern matching in compressed text.

This data compression method doesn't transform the text in a complex way, but just erases some symbols. From the single point of view it could be possible to erase just some symbols from the searched pattern and look for it. This is really possible, but with some limitations, because what symbols we erase depends also on the current context. If we search for a long pattern, we can utilize its synchronizing property, from which we obtain:

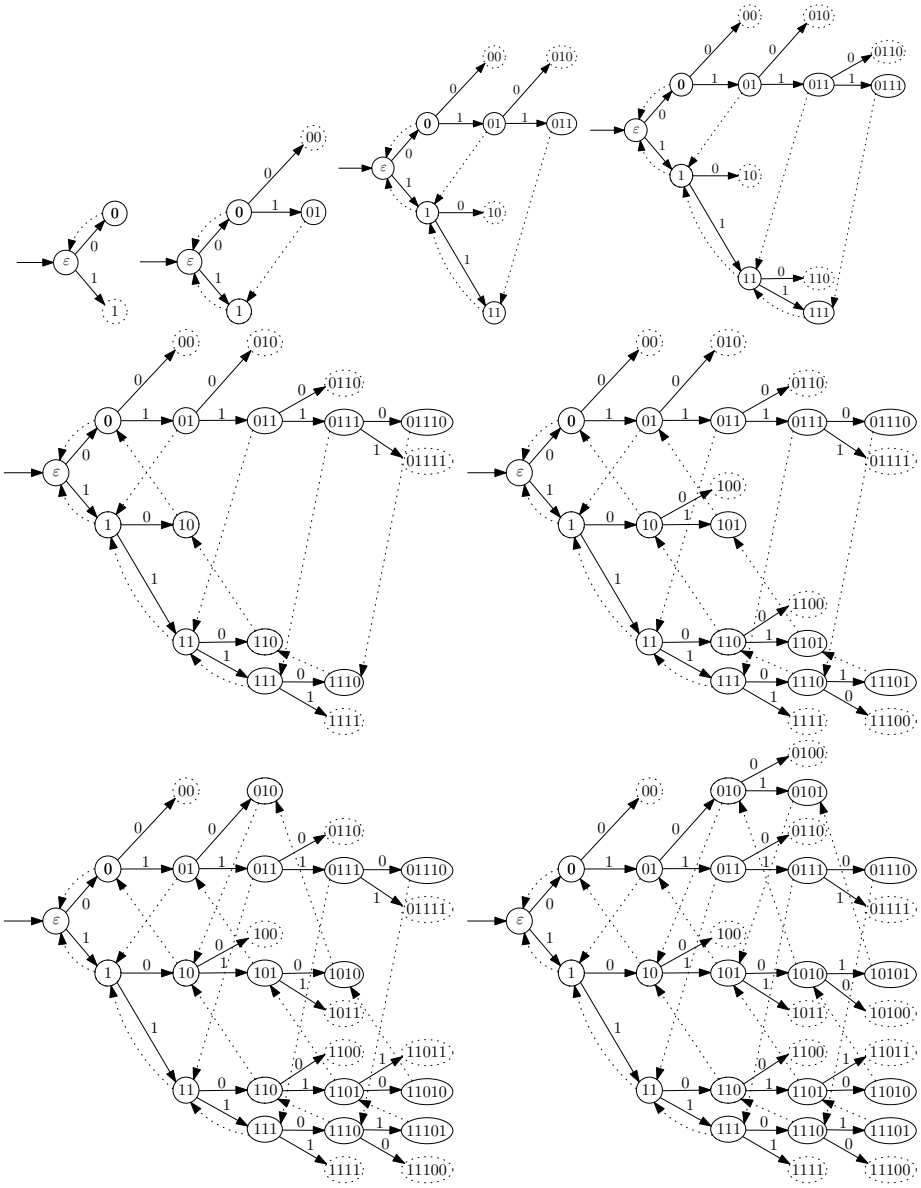

Figure 3.11: Suffix trie construction over text 01110101 for dynamic compression

Lemma 3.1 (Synchronizing property [17])
If $|w| \geq k-1$, then $\delta^*(u,w) = \delta^*(root,w)$ for any state $u \in Q$ such that $\delta^*(u,w) \notin AD$, where w is the searched pattern, k is length of the longest forbidden word in the antidictionary, Q is the set of all compression/decompression transducer states, function $\delta^*(u,w)$ is the state reached after applying all transitions $\delta(u_i, b_i), i = 1 \ldots i_{|w|}, u_1 = u, u_i = \delta(u_{i-1}, b_{i-1}), w = b_1 b_2 \ldots b_{|w|}, b \in \{0,1\}$.

Unfortunately this works only for patterns longer than k, so we need to search the compressed text using a different technique presented in [17], which solves the problem in $\mathcal{O}(m^2 + \|M\| + n + r)$ time using $\mathcal{O}(m^2 + \|M\| + n)$ space, where m and n are the pattern length and the compressed text length respectively, $\|M\|$ denotes the total length of strings in antidictionary M, and r is the number of pattern occurrences.

This is achieved using a decompression transducer with eliminated ε-states similar to the one mentioned in [8] and an automaton build over the search pattern. The algorithm has a linear complexity proportional to the compressed text length, when we exclude the pattern processing. This pattern searching algorithm can be used on texts compressed using static compression method, because it needs to preprocess the antidictionary before searching starts, not on texts produced by dynamic method, which also lacks synchronization property of static compressed texts.

Chapter 4

Implementation

4.1 Used Platform

The main target of this thesis was to implement a working DCA implementation, try different parameters of the method and choose the most appropriate. Program was intended to work on command line and be as efficient as possible. Many tests were needed to run as a batch, the program was to be licensed under some public licence, and that's why GNU/Linux platform for selected for development. Also small memory requirements, low CPU usage and other optimization factors were demanded.

As C/C++ is a native language for development on most platforms, C++ language using *gcc* compiler (*g++* respectively), which also suits best for its built-in optimizations, was preferred. Using C++ we have memory management of dynamically allocated memory in our hands, we don't need to rely on a garbage collector. The program was developed for 32 bit platforms, it would need further modifications to work under 64 bit environment. For good portability GNU tools *Automake* and *Autoconf* were used, that automatically generate build scripts for target platform. The program was tested only under *i586* platform, which uses little endian, for big endian platforms modifications would be needed. Nevertheless this program serves still rather for research and testing purposes, it is not usable as a production tool, despite the efforts it is not practically usable because of its high system resources requirements. As the code is published under GNU/GPL, everyone can use the code, experiment with it and try to improve it.

4.2 Documentation and Versioning

Because program code was changing a lot during development, a versioning system *Subversion*, which remembers all the changes, can find differences to the current version or provide a working version from the past, was used. This ability was used more than once, as to get the algorithm working correctly is quite difficult. Huge data structures are built in the memory, suffix tries are modified online, traversed in different ways and

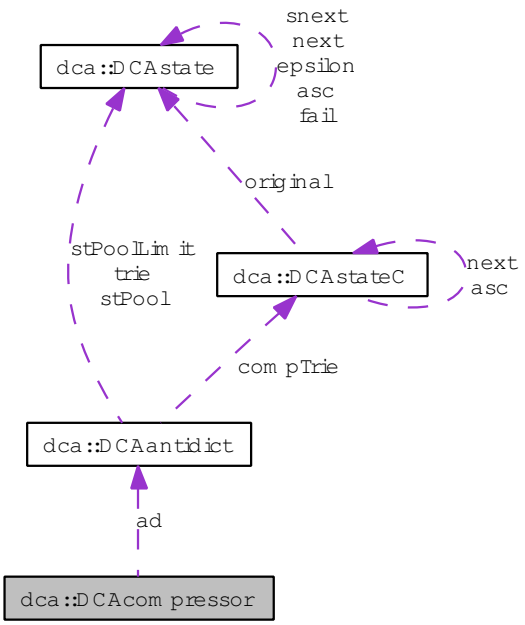

Figure 4.1: Collaboration diagram of class *DCAcompressor*

directions and it is a challenge to debug what is really going on. Although we can verify compressed data by decompressing them, this doesn't tell us anything about optimal selection of forbidden words or correct and complete building of the data structure for representing all text factors.

Documentation was written along with the code using documentation generator *Doxygen*. This documentation generator takes the program source code, extracts all classes, functions and variables definitions and provides them with comments specified in the source, output formats are HTML and LaTeX. Unlike offline documentation systems *Doxygen* keeps the documentation up-to-date. An example of collaboration diagram of class `DCA` created by Doxygen in cooperation with *Graphviz* can be seen on Figure 4.1.

We can't rely just on this type of documentation, as it does not describe, how the algorithms work in common, only describes the meaning of each variable and how the functions are called. For that type of documentation some *Wiki* system, LaTeX or another kind of offline documentation is more appropriate. It should also support including tables and graphics for better descriptions of used data structures and algorithms. At this point this text is serving for this purpose.

4.3 Debugging

As was mentioned before, it was needed to debug, how the program was really performing some tasks, including building trie and its online modification. Normal program debuggers as `gdb` are not very useful, as we need to see the program outputs and contents of

large data structures contained in memory. Therefore the program was equipped with different debugging options to provide information about each part of the process, they can be turned on in compile time by defining the following macros:

- `DEBUG` – if not set, turns off all debugging messages, otherwise shows debugging messages according to `LOG_MASK` filter; also enables counters of total nodes and nodes deleted during simple pruning,
- `DEBUG_DCA` – enables trie and antidictionary debugging, every node contains also its complete string representation, which enlarges memory requirements a lot,
- `PROFILING` – turns on/off profiling info designated for performance measurements.

Profiling is using POSIX `getrusage()` function and reads `ru_utime` and `ru_stime` representing user time and system time used by the current process. These times are measured at the beginning and at the end of the measured program part, if the procedure runs more times, the measured time is accumulated. For this purpose classes `TimeDiff_t` and `AccTime_t` are provided, the first measures time interval, the second measures accumulated time. What we need to know, is that using `getrusage()` function also influences the program performance, especially the accumulated time measurement of a program part repeated many times. With `--verbose` option the program reports the whole time taken to perform the operation as well as antidictionary size and compression ratio achieved.

CPU time consumption is just one part of system requirements, what we are very interested in, too, is a memory consumption. It was measured using `memusage` utility that comes from the GNU libc development tools and it is a part of many GNU/Linux distributions. This tool reports the peak memory usage of heap and stack extra. What we are interested in more is the heap peak size, as the most memory used is allocated dynamically. Also the amount of allocated and correctly deallocated memory could be seen. But in fact we don't really need to check it as the program compresses only one file at a time and the memory is automatically deallocated when the program terminates.

For debugging purposes `LOG_MASK` was introduced to have the ability to select what we really want to debug and not to be choked up with other extensive useless debug messages. `LOG_MASK` is a set of the following items:

- `DBG_MAIN` – print information about which part of the algorithm is currently being run,
- `DBG_TRIE` – debug suffix trie data structures and displays its contents in different parts of algorithm; it also exports the contents into *graphviz* graph file language for drawing directed graphs using *dot* tool,
- `DBG_COMP` – debug compression process, shows read symbols, used transitions in compression transducer, compressed symbols,
- `DBG_DECOMP` – debug decompression process, shows read symbols, used transitions and symbol output,

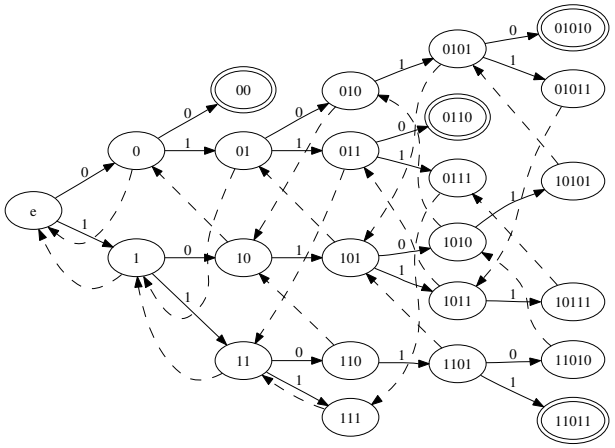

Figure 4.2: Suffix trie for text "11010111" generated by *graphviz*

- `DBG_PRUNE` – debug simple pruning process, gain computation, traversal over the suffix trie, tested and pruned nodes,
- `DBG_AD` – prints antidictionary and self-compressed antidictionary contents in different stages of algorithm, such as before and after simple pruning,
- `DBG_STATS` – print some useful statistics, like results of simple pruning, antidictionary self-compression and overall algorithm performance,
- `DBG_ALMOSTAW` – debug almost antifactors related information,
- `DBG_PROFILE` – show profiling info.

One of the most useful options is the antidictionary debugging, which stores antidictionary state in different stages to an external file for later examination. From this we can find out if the antidictionary construction is working properly or which antiwords are problematic. With this we have an essential hint for finding implementation errors.

Another important option is the trie debugging, which outputs a trie structure in a text format as well as in a graphical format created using graphviz[1]. It is possible to even watch the suffix trie construction step by step. Regardless these graphs are drawn automatically and are not so nice as diagrams drawn by hand, they can be still very handy. An example of a suffix trie graph generated by graphviz can be seen on Figure 4.2.

4.4 Implementation of Static Compression Scheme

In Section 3.5 has been already outlined how the antidictionary and compression transducer is prepared for static compression scheme. Let's look at overview what we actually

[1] Graph Visualization Software — open source graph (network) visualization project from AT&T Research, http://www.graphviz.org/

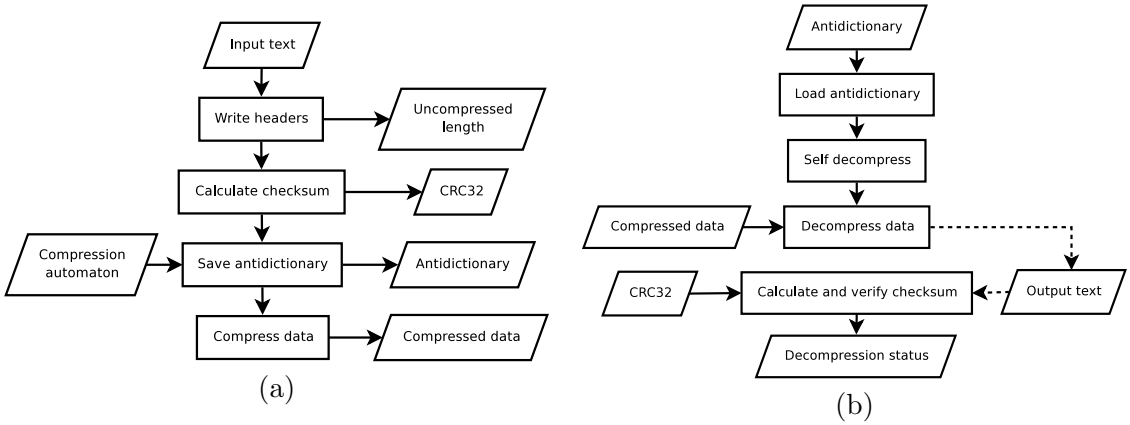

Figure 4.3: File compression (a) and file decompression (b) schemes

do with a ready-made transducer. In Figure 4.3 both compression and decompression process schemes can be found, examining both processes further.

With static compression scheme after building the antidictionary and compression transducer we have already read the whole text, we know its length and we can easily compute its CRC32 checksum while building the antidictionary. As the decompression process needs to know the length of original data, we save this, along with CRC32 for verifying data integrity, into the output file. Then we save the antidictionary using one of the methods discussed in Section 4.5. And only after this we start compressing the input data using the compression transducer and writing its product to the output file.

The decompression process should be clear. First we read the data length, CRC32 and we load the antidictionary into the memory in a suffix trie representation. Then we self-decompress the trie updating all suffix links and creating decompression transducer at a time. With prepared transducer we run decompression until we get `originalLen` amount of data, writing the product to output file and calculating CRC32 of decompressed data. At the end we verify the checksum and notify user of decompression result (`CRC OK` or description of which error occurred).

In Section 3.5 antidictionary construction process has been presented, but it was not complete. Actually "Build Automaton" phase must be executed one more time just after "Build Antidictionary" stage to fix all incorrect suffix links and forward edges pointing to removed nodes, as they are required for self-compression. After this correction, antidictionary construction with single self compression and single simple pruning round looks like this: Figure 4.4. Now individual stages will be described in more detail.

4.4.1 Suffix trie construction

For suffix trie construction an algorithm very similar to the one presented in [6] is used. Function *Build-Fact*() reads input and builds suffix trie adding new nodes, $fvis(r)$ is direct visits count of node r. Function *Next*() takes care of creating all suffix links and

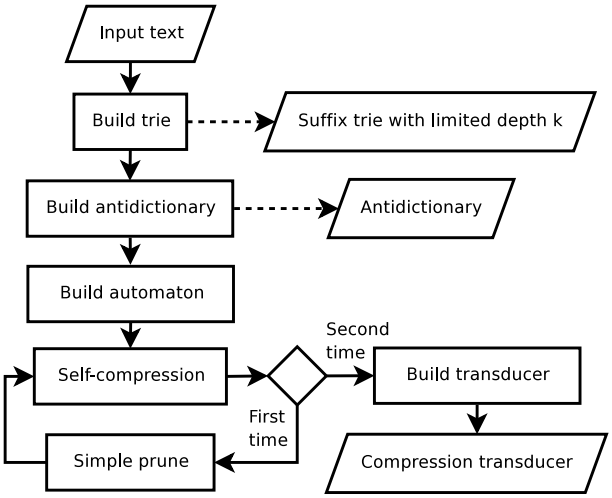

Figure 4.4: Real implementation of static scheme antidictionary construction with self-compression and single simple pruning

missing nodes up to the root node. $b(r)$ is the input symbol leading to node r, *visited*(r) is total visits of the node, used later for gain computation, *asc*(r) is parent of node r, *fail*(r) is suffix link of node r. *antiword*(r) and *deleted*(r) indicate node status, *awpath*(r) indicates, if there exists a path from root node to some antiword through node r. Time asymptotic complexity of *Build-Fact*() is $\mathcal{O}(N * k)$.

```
1   Build−Fact (int maxdepth > 0)
2       root ← new state;
3       level(root) ← 0; fvis(root) ← 0; visited(root) ← 0;
4       deleted(root) ← false; antiword(root) ← false; awpath(root) ← false;
5       cur ← root;
6       while not EOF do
7           read(a);
8           cur ← Next(cur, a, maxdepth);
9           fvis(cur) ← fvis(cur) + 1;
10      return root;

1   Next (state cur, bool a, int maxdepth > 0)
2       if δ(cur, a) defined then
3           return δ(cur, a)
4       else if level(cur) = maxdepth then
5           return Next(fail(cur), a, maxdepth)
6       else
7           q ← new state;
8           level(q) ← level(cur) + 1; fvis(q) ← 0; visited(q) ← 0; b(q) ← a;
9           deleted(q) ← false; antiword(q) ← false; awpath(q) ← false;
10          δ(cur, a) ← q;
11          if cur = root then fail(q) = root;
12          else fail(q) ← Next(fail(cur), a, maxdepth);
13          return q;
```

struct DCAstate
DCAstate* next[0..1]
DCAstate* snext[0..1]
DCAstate* fail
DCAstate* asc
DCAstate* epsilon
int visited, fvis, level
bool b, awpath, antiword

(a)

struct DCAstateC
DCAstateC* next[0..1]
DCAstateC* asc
DCAstate* original
int gain
bool b

(b)

Table 4.1: *DCAstate* structure (a) representing a suffix trie node and *DCAstateC* structure (b) representing a node in self-compressed trie

Suffix trie nodes are represented by *DCAstate* structure (Figure 4.1a), *next* represents δ transitions, *snext* represents δ', *epsilon* represents ε transitions, other variables represent functions with corresponding names. For representation of nodes in self-compressed trie there is used another structure — *DCAstateC* (Figure 4.1b), which is more efficient, meaning of variables is similar to *DCAstate* variables, *original* is a pointer to an original node in non-compressed trie.

4.4.2 Building antidictionary

Function *Build-AD*() walks through the tree and adds all minimal antifactors. Using function *MarkPath*() it marks all nodes in the path from root node to the antiword. Then using traversal in depth-first order it computes node total visits and removes all nodes, that does not lead to any antiword. We also omit *stopping pair* antifactors as they don't bring any compression. Time asymptotic complexity of *Build-AD*() is $\mathcal{O}(N * k^2)$, which makes it strongly dependant on *maxdepth* k.

```
1   Build−AD (root)
2       for each node p, level(p) < k in breadth−first order do
3           for a ∈ {0,1} do
4               if δ(p,a) defined then
5                   δ'(p,a) = δ(p,a)
6               else if δ(fail(p), a) defined and δ(p,ā) defined then
7                   q ← new state;
8                   δ'(p,a) ← q;
9                   antiword(q) ← true;
10                  MarkPath(q);
11      for each node p, not antiword(p) in depth−first order do
12          if fvis(p) > 0 then
13              vis ← 0;
14              q ← p;
15              while q ≠ root
16                  if fvis(q) > 0 then
17                      vis ← vis + fvis(q);
18                      fvis(q) ← 0;
```

```
19                  q ← fail(q);
20                  visited(q) ← visited(q) + vis;
21              if not awpath(p) then
22                  if asc(p) defined then
23                      δ′(asc(p), b(p)) ← NULL;
24                  deleted(p) ← true;
```

```
1   MarkPath(p)
2       while p defined and not awpath(p) do
3           awpath(p) ← true;
4           p ← asc(p);
```

4.4.3 Building automaton

After building antidictionary and removing all nodes not leading to antiwords, the trie is not consistent, some of the suffix links are pointing to deleted nodes. This has to be fixed before self-compressing the trie. At the same time we correct the suffix links, we also define new δ transitions and ε transitions creating a compression transducer. Time asymptotic complexity of *Build-Automaton* is $\mathcal{O}(N * k)$.

```
1   Build−Automaton (root)
2       for a ∈ {0, 1} do
3           if δ′(root, a) defined and not deleted(δ′(root, a)) then
4               δ(root, a) ← δ′(root, a);
5               fail(δ(root, a)) ← root;
6           else
7               δ(root, a) ← root;
8       if antiword(δ(root, a)) for a ∈ {0, 1} then
9           ε(root) ← δ(root, ā);
10      for each node p, p ≠ trie in breadth−first order do
11          for a ∈ {0, 1} do
12              if δ′(p, a) defined and not deleted(δ′(p, a)) then
13                  δ(p, a) ← δ′(p, a);
14                  fail(δ(p, a)) ← δ(fail(p), a);
15              else if not antiword(p)
16                  δ(p, a) ← δ(fail(p), a);
17              else
18                  δ(p, a) ← p;
19          if not antiword(p) then
20              if antiword(δ(p, a)) for a ∈ {0, 1} then
21                  ε(p) ← δ(p, ā);
```

4.4.4 Self-compression

Using self-compression we create a new compressed trie from the original trie and initialize gain values $g'(r)$ of all nodes to -1. This is necessary for the simple-pruning algorithm, as it walks the trie bottom-up and needs to know, if both subtrees were already processed.

The *original*(r) value is a pointer to the original code in non-compressed suffix trie. Time asymptotic complexity is $\mathcal{O}(N * k)$.

```
1   Self−Compress (root)
2       rootCompr ← new state;
3       add (root, rootCompr) to empty queue Q;
4       while Q ≠ ∅ do
5           extract (p,p′) from Q;
6           if q0 and q1 are children of p then
7               create q′0 and q′1 as children of p′;
8               original(q′0) ← q0; original(q′1) ← q1;
9               g′(q′0) ← −1; g′(q′1) ← −1;
10              add (q0, q′0) and (q1, q′1) to Q;
11          else if q is a unique child of p, q = δ(p, a), a ∈ {0, 1} then
12              if antiword(δ(p, ā)) then
13                  add (q, p′) to Q;
14              else
15                  create q′ as a−child of p′;
16                  original(q′) ← q;
17                  g′(q′) ← −1;
18                  add (q, q′) to Q;
19      return rootCompr;
```

4.4.5 Gain computation

Gain computation is based on the fact, that we can estimate gain of a node being an antifactor, if we know how much costs its representation. For this $2 + 2$ representation is used for antidictionary storage, described in Section 4.5. Gain $g'(S)$ of subtree S is defined as in [6]:

$$g'(S) = \begin{cases} 0 & \text{if } S \text{ is empty,} \\ c(S) - 2 & \text{if } S \text{ is a leaf (antiword),} \\ g'(S_1) - 2 & \text{if } S \text{ has one child } S_1, \\ M & \text{if } S \text{ has two children } S_1 \text{ and } S_2, \end{cases}$$

where $M = max(g'(S_1), g'(S_2), g'(S_1) + g'(S_2)) - 2$. It is clear, that it is possible to compute gains in linear time with respect to the size of the trie in a single bottom-up traversal of the trie. But how the self-compression affects our gain computation? The answer is, that it doesn't in fact, we simply compute the gains using the self-compressed tree!

4.4.6 Simple cruning

Simple pruning function prunes from the trie all nodes which does not have positive gain. Gain function is computed using the self-compressed trie. As we are walking the trie bottom-up from terminal nodes, the traversal is not deterministic and it's not

guaranteed, that in each node we process, gains of both subtrees are already computed. For this we have set $g'(r)$ of each node r to value -1, which means uninitialized value, if we hit a node with an uninitialized subtree, we stop walking bottom-up and continue with the next antiword. After processing all antiwords, all trie nodes will have a defined gain.

Whenever we find a node with negative gain, we prune it with the whole subtree belonging to it and at the same time we prune also the subtree from the orginal trie. As we forbid nodes with negative gains, we can simplify function $M = max(g'(S_1), g'(S_2), g'(S_1) + g'(S_2)) - 2$ from Section 4.4.5 to $M' = g'(S_1) + g'(S_2)$.

Because this is not the only one possibility of static compression scheme implementation, for testing purposes simple-pruning was implemented also without self-compression. Because it is very similar to the version using self-compression, only the more interesting version of simple pruning the self-compressed trie is going to be presented. Using $\mathcal{O}(N)$ for antidictionary size according to [14] and $\mathcal{O}(2^k)$ for pruning subtree we get time asymptotic complexity $\mathcal{O}(N * k * 2^k)$.

```
1   Simple−Prune (rootCompr)
2       for each node p, antiword(p) do
3           while p ≠ rootCompr do
4               q ← asc(p);
5               if antiword(original(p)) then
6                   g′(p) ← visited(asc(original(p))) − 2
7               else if p has children p1, p2 then
8                   if g′(p1) = −1 or g′(p2) = −1 then
9                       break;
10                  g′(p) ← g′(p1) + g′(p2) − 2
11              else if p has child pp then
12                  if g′(pp) = −1 then
13                      break;
14                  g′(p) ← g′(pp) − 2;
15              if g′(p) <= 0 then
16                  prune subtree p; prune subtree original(p);
17              p ← q;
```

4.5 Antidictionary Representation

In static compression scheme we need to provide the compressed data with the andictionary used for compression in order to be able to decompress it. And as the antidictionary size reaches about 50% of the compressed data length, we know antidictionary is really important and has a great significance to the final compression ratio. As in the original paper *2+2* representation is used, but other possibilities are also discussed.

- *antiword list* – probably the least efficient storage for antiwords, it is not using any common prefixes, but has better abilities for self-compression, as mentioned in Section 3.5.2.

- *2+2* – binary tree with k nodes is encoded using $2k$ bits for the whole tree. Using depth-first order we encode in each node, if it has both subtrees, only the right subtree, only the left subtree or no subtree, by the strings 00, 01, 10, 11.

- *3+1* – representation introduced in [7], we traverse the tree in depth-first order and write a 1 bit each time we find an internal node and a 0 bit each time we find an external node. Therefore, a binary tree of m internal nodes will need exactly $2m+1$ bits, which is almost identical to the *2+2* scheme.

- *Hamming coding* – first we walk the trie in depth-first order and count the times we go left, right and up. Then we compute Hamming coding for these directions and encode the trie by a depth-first walk. After experiments with this coding, we found, that it is better only on very unbalanced trees, in other cases it performs worse then *2+2*.

- *Text Generating the Antidictionary* – an interesting idea, of how to code an antidictionary, is to supply some short text, that generates the target antidictionary. This representation could be very efficient, this option is going to be discussed more thoroughly.

In this DCA implementation *2+2* representation was used with the following meaning:

code	meaning
00	no subtree
01	only the right subtree
10	only the left subtree
11	both subtrees

4.5.1 Text generating the antidictionary

While playing with antidictionaries and their automata a new possibility of representing antidictionaries was thought up. It seems to be feasible to code the antidictionary even more efficiently. Such antidictionary would be generated from a special text and then this antidictionary would be used for text decompression. The idea is based on fact, that for an antidictionary $AD \neq \emptyset$ generated from string T_x, whose automaton contains cycles, there exists some string T_y, which generates the same antidictionary AD, $T_x \neq T_y$, $|T_y| \leq |T_x|$.

To be more efficient than representation R, we need to find a text T_y generating antidictionary AD, $|T_y| < rsize(R, AD)$, where *rsize* is number of bits used by representation R to code antidictionary AD. Problem is that this method probably won't work for general pruned antidictionaries. An in-depth future research on this topic is needed. Another problem is, that the generating text T_y should contain the original *stopping pair*. Different text ending could lead to new unwanted antiwords. An example of antidictionary whose compression/decompression transducer contains a loop is provided.

size	item	description
3B	"DCA"	text identificator to unambiguously identify DCA compressed file
4B	original length	length of the original input text, this length is important when decompressing data to determine end of the decompression process
4B	CRC32	cyclic redundancy check of the original data, it is computed and checked during decompression
*	antidictionary	antidictionary representation as specified in Section 4.5
*	compressed data	data with bits erased using DCA compression

Table 4.2: Compressed file format

Example 4.1
Let's suppose that we have an antidictionary AD built over string "01010101", $AD = \{00, 11\}$. If we encodeded it using *2+2* representation, we would get antidictionary size $|AD| = 2 * k = 10$ bits, as the trie has $k = 5$ nodes. It is easy to see, that the text "010" generates the same antidictionary, while it needs only 3 bits for coding the generating text and a few bits for coding the text length.

Two promising ways of generating text T_y were found. The first uses compression transducer processing input text T_x avoiding loops, that don't bring new nodes into suffix trie. The second walks back from the *stopping pair* using transitions and suffix links in inversed directions until it walks through all nodes. Both methods may not work on general suffix tries, rather on the non-pruned constructed from a real text string, but this needs more experiments.

Disadvantage of this representation is slower decompression, because we need to build the antidictionary first from text T_y, also the decompressor must use the same method as compressor to reconstruct the antidictionary. Another problem could be complexity of constructing text T_y in compression process. Still antidictionary representation using a generating text looks promising.

4.6 Compressed File Format

To be able to store the files compressed using DCA, a compressed file format had to be developed. The proposed file format is similar to the one used by *gzip* and contains only the necessary fields, targeting it to representing files compressed by static compression scheme. CRC32 is used to check integrity of the decompressed data. See Table 4.2.

4.7 Antidictionary Construction Using Suffix Array

4.7.1 Suffix array construction

In these days we have a choice between many algorithms for suffix array construction. They were a subject to test in [16], according which the used implementation were chosen. Problem is that these algorithms are designated to 8 bit symbols, while we need just 0's and 1's for antidictionary construction. It was obvious that it was necessary to make some modifications to the existing implementation to handle binary alphabet.

According to the paper [16], none of the new linear time construction algorithm would be a good choice for their large constants and memory requirements, instead a highly optimized Manzini-Ferragina implementation [13] with non-linear asymptotic complexity in almost all the tests performed better in both memory consumption and CPU time used. Their implementation using C was modified to compile under C++ and also adjusted the algorithm to use just 1 bit symbols, instead of 8 bits in input text. Corrections were applied to deep sort, shallow sort and bucket sort subroutines. LCP algorithm did not need this adjustment. But because the whole algorithm wasn't examined well, after this 8 bit to 1 bit modification, the whole algorithm could be not optimal now. This would need a further study and may be some more optimal algorithm for computing suffix array of a bit array could be developed.

The whole byte is now used for representation of just a single bit, that means the algorithm is now wasting 7 bits for each single bit of input text. Addressing single bits in bytes was not tested, but it is very likely that addressing a single bit and swapping bits would need more CPU time, while memory occupied by the whole input text expanded 8 times is still marginal in comparison with the total memory needed for representing the compression transducer.

4.7.2 Antidictionary construction

Anyway we have a working suffix array construction algorithm and we are going to use it for antidictionary construction. An outline of antidictionary construction using the suffix array was already presented in Section 3.6. In this implementation functions *Build-AD-SA*(), *SA-Bin-Search*() and *Add-Antiword*() are used, where the first one is the most important doing most of the job finding all possible antifactors, *SA-Bin-Search*() checks if the antifactor is minimal and *Add-Antiword*() adds the new antiword to the suffix trie and computes visit counts of the added nodes. Symbol '#' denotes end of string, function *substr*(str, ind, len) returns substring of string *str* starting at position *ind* of length *len*, functions *makeSA*() and *makeLCP*() return suffix array and LCP array for specified text.

Time asymptotic complexity of *Build-AD-SA* is $\mathcal{O}(k * N(\log N + k))$, which is similar to complexity of building antidictionary from suffix trie, but with memory requirements $\mathcal{O}(N)$ thanks to suffix array representation. This assumpts, that we are able to count number of node visits in $\mathcal{O}(k)$, which can be done during walking through the suffix+lcp array. In this implementation it is $\mathcal{O}(N)$ in worst case, but in average it is much smaller,

this implies total asymptotic complexity $\mathcal{O}(k * N(N + \log N))$.

```
1   Build−AD−SA (root, int crc, int maxdepth > 0)
2       read whole input → bittext;
3       crc ← computeCRC32(bittext);
4       expand each single bit in bittext to 1 byte;
5       sa ← makeSA(bittext); lcp ← makeLCP(bittext, sa);
6       root ← new state; level(root) ← 0; fail(root) ← root;
7       for i ← 0 to |sa| do
8           lo ← 1; hi ← |sa|; l ← lcp[i + 1];
9           if l = maxdepth then
10              continue;
11          w_cur ← substr(bittext, sa[i], maxdepth);
12          w_next ← substr(bittext, sa[i + 1], maxdepth);
13          if w_cur[l] = '#' then {end of current word}
14              if w_next[l] = '1' then { '#'→'1'}
15                  aw ← substr(w_next, 0, l) . '0';
16                  if SA−Bin−Search(bittext, sa, aw, lo, hi) then
17                      Add−Antiword(root, lcp, aw, i + 1);
18          else if w_next[l] = '#' then {end of next word}
19              if w_cur[l] = '0' then { '0'→'#'}
20                  aw ← substr(w_cur, 0, l) . '1';
21                  if SA−Bin−Search(bittext, sa, aw, lo, hi) then
22                      Add−Antiword(root, lcp, aw, i);
23          lo2 ← lo; hi2 ← hi;
24          for ll ← l + 1 to |w_cur| − 1 do
25              if (w_cur[ll] = '0') then
26                  aw ← substr(w_cur, 0, ll) . '1';
27                  if SA−Bin−Search(bittext, sa, aw, lo, hi) then
28                      Add−Antiword(root, lcp, aw, i);
29          for ll ← l + 1 to |w_next| − 1 do
30              if w_next[ll] = '1' then
31                  aw ← substr(w_next, 0, ll) . '0';
32                  if SA−Bin−Search(bittext, sa, aw, lo2, hi2) then
33                      Add−Antiword(root, lcp, aw, i + 1);
34      if |sa| > 0 then {process the last word}
35          lo ← 1; hi ← |sa|;
36          w_cur ← substr(bittext, sa[|sa| − 1], maxdepth);
37          for l ← 0 to |w_cur| − 1 do
38              if w_cur[l] = '0' then
39                  aw ← substr(w_cur, 0, l) . '1';
40                  if SA−Bin−Search(bittext, sa, aw, lo, hi) then
41                      Add−Antiword(root, lcp, aw, |sa| − 1);
```

```
1   SA−Bin−Search (bittext, sa, aw, lo, hi)
2       pos ← 0;
3       tofind ← substr(aw, 1, |aw| − 1);
4       while hi ≥ lo do {at first find |tofind| − 1 characters}
5           pos ← (hi + lo)/2;
6           if sa[pos] + |tofind| − 1 < |sa| then
7               str ← substr(bittext, sa[pos], |tofind| − 1);
8               if str = substr(tofind, 0, |str|) then
9                   break;
```

```
10                  else if str < substr(tofind, 0, |str|) then
11                      hi ← pos − 1;
12                  else
13                      lo ← pos + 1;
14              else
15                  str ← substr(bittext, sa[pos], |sa| − sa[pos]);
16                  if str < substr(tofind, 0, |str|) then
17                      hi ← pos − 1;
18                  else
19                      lo ← pos + 1;
20          if hi < lo then
21              return false;
22          lo2 ← lo; hi2 ← hi;
23          while hi2 ≥ lo2 do {find exact string}
24              pos ← (hi2 + lo2)/2;
25              if sa[pos] + |tofind| < |sa| then
26                  str ← substr(bittext, sa[pos], |tofind|);
27                  if str = substr(tofind, 0, |str|) then
28                      break;
29                  else if str < substr(tofind, 0, |str|) then
30                      hi2 ← pos − 1;
31                  else
32                      lo2 ← pos + 1;
33              else
34                  str ← substr(bittext, sa[pos], |sa| − sa[pos]);
35                  if str < substr(tofind, 0, |str|) then
36                      hi2 ← pos − 1;
37                  else
38                      lo2 ← pos + 1;
39          if hi2 < lo2 then
40              return false;
41          return true;
```

```
1       Add−Antiword (root, lcp, aw, saPos)
2           p ← root;
3           for i ← 0 to |aw| − 1 do
4               if δ′(p, aw[i]) not defined then
5                   q ← new state; asc(q) ← p; level(q) ← i + 1;
6                   δ′(p, aw[i]) ← q;
7                   p ← q;
8               else
9                   p ← δ′(p, aw[i]);
10          antiword(p) ← true;
11          j ← saPos; k ← saPos;
12          len ← |aw| − 1;
13          while lcp[j] ≥ len do
14              j ← j − 1;
15          while k < n and lcp[k + 1] ≥ len do
16              k ← k + 1;
17          visited(asc(p)) ← k − j + 1;
```

4.8 Run Length Encoding

As discussed before, classical DCA approach has a problem with compressing strings of type 0^n1, although it compresses well string 1^n0. We can improve these simple repetitions handling by including RLE compression before the input of the DCA algorithm. Run length encoding is a very simple form of lossless data compression in which *runs* of data, i.e. sequences of the symbol, are stored as a single data value and count, rather than as the original run. We compress all sequences with length ≥ 3 with count encoded using *Fibonacci code* [2]. Sequences shorter than 3 are kept untouched.

Example 4.2
Compress text "abbaaabbbbbbbbbbbbbba" $= ab^2a^3b^{15}a$ using RLE.

In the input text there are two sequences with length ≥ 3, a^3 and b^{15}. We compress the first as "aaa0", zero means no other "a" symbols. We compress the second sequence in a similar way, resulting in "bbb12". Our compressed text will be "abbaaa0bbb12a".

4.9 Almost Antiwords

In order to improve the compression ratio also the almost antiwords improvement discussed in Section 3.7 was tested implementing the one-pass heuristics. It is based on the suffix trie implementation, but an algorithm for building antidictionary with almost antiwords support could be probably also developed.

The results were little disappointing at the beginning, later showed up that the modified algorithm performs very good on some types of texts, while being worse than classical approach on others. Another significant issue is, that the gain of almost antiwords is based on an unknown factor of exception length, which can be only roughly estimated. Fine tuning this implementation would probably lead to better results. For coding exceptions *Fibonacci code* [2] was used again.

4.10 Parallel Antidictionaries

Unlike classical dictionary compression algorithms working with symbols, DCA is working with a binary stream, where each considered symbol can gain only values '0' and '1'. This is very limiting, because we lose notion of symbol boundaries in text, as most English text documents use only 7 bit symbols and we could just forget about the 7th bit, as it remains '0'. What was subject to test, was to slice a file lengthwise creating 8 files "fileN" with 0th bit in "file0", 1st bit in "file1" and so on, and then compressing these portions separately using different antidictionaries. Using these approach 8 parallel antidictionaries over a single file were simulated.

4.11 Used Optimizations

To optimize the code, some well-known optimizations as pointer arithmetics when working with arrays, loop unrolling, dynamic allocation in large pools of prepared data were used. Dynamic allocation has a significant impact on the performance, that's why more memory than needed is allocated at a time. Compiler optimizations were used, too, it is even possible to use profiler log to gain better performance.

4.12 Verifying Results

During development many compression problems occurred. For verifying results extensive logging was used and also some tools for checking the algorithm performance had to be written, such as antidictionary generation, self-compression results and gain computation. The best verification we have is, that after decompression we get the original text, however this tells us nothing about the optimality of the used antidictionary. It has to be checked some other way.

After antidictionary construction using suffix array was implemented, there has been an advantage of two completely different methods for generating the antidictinary. Comparing outputs of these two different algorithms gives us a very good hint, if the generated antidictionary is correct. So to verify the complete antidictionary is quite easy, but verification of the simple pruning process is impossible in fact, as there is no algorithm for constructing the most efficient antidictionary available.

It's much easier with self-compression. Self-compression check was implemented using a dummy python script, which compresses all antiwords using all shorter ones. Performance is quite slow, but the result is sufficient.

Also after code rewriting or implementing something new the new code has to be tested every time on a set of files if it compresses and decompresses them correctly. This all was possible thanks to strong scripting abilities of the GNU/Linux environment and without all the verification tools it would not be so easy.

4.13 Dividing Input Text into Smaller Blocks

Earlier the memory greediness of DCA method and some options of reducing these requirements were discussed. Still one of the simplest options is to divide the file into smaller blocks and compress them separately. This will reduce memory requirements a lot, as the trie memory size depends strongly on the length of input text. On the other hand we need to realize that this will affect compression ratio, which will be worse, because the antidictionary will be smaller and the gains of antifactors will be lower.

Chapter 5

Experiments

5.1 Measurements

All measurements were executed on an AMD Athlon XP 2500+, 1024MB RAM, with Mandriva Linux and kernel version 2.6.17 i686. All time measurements were made 5 times, for time measurements the minimal achieved value was selected, for memory measurements only one measurement was sufficient, as the algorithm is deterministic and use the same amount of memory every time for the same configuration. Memory was measured using *memusage* from GNU libc development tools summarizing heap and stack peak usage. Time was measured using *getrusage*() as a sum of user and system time used. Program was compiled with "-O3" and DEBUG, PROFILING, MEASURING options turned on and all debug logging turned off. Program was called with "-v" option displaying summary with compressed data length, antidictionary size, compression ratio achieved and total time taken.

We are going to choose appropriate parameters for static as well as dynamic compression scheme. In static compression scheme we have parameters *maxdepth*, how to use self-compression and whether to use suffix array. In dynamic compression scheme we can affect only *maxdepth*.

5.2 Self-Compression

Self-compression is one of the static compression scheme parameters. Using self-compression is not mandatory, so we can skip it and use *simple pruning only*. Another option is to use it together with simple pruning, we will denote it as *single self-compression*. For better precision we can use self-compression and simple pruning as long we prune some antiwords from the trie, we call this *multiple self-compression*.

Following tests were performed over "paper1" file from "Calgary Corpus". In Figure 5.1 we can see that *simple pruning only* requires more memory than methods using self-compression. In Figure 5.2 we can see, that *simple pruning only* is the fastest, but the

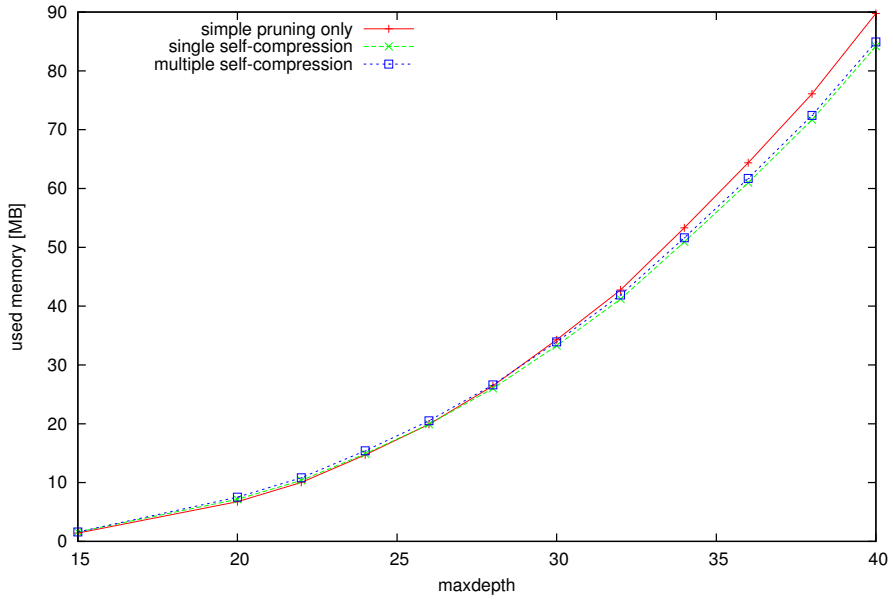

Figure 5.1: Memory requirements of different self-compression options

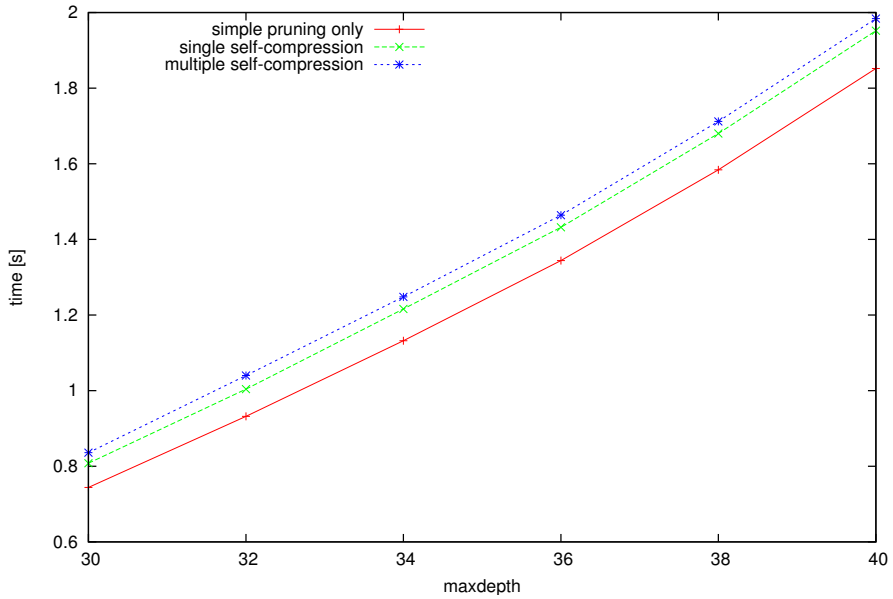

Figure 5.2: Time requirements of different self-compression options

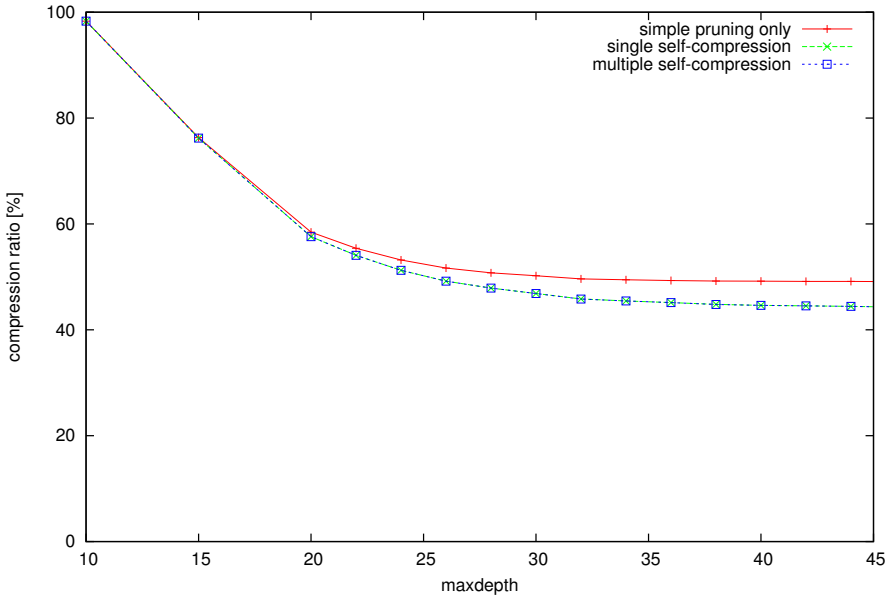

Figure 5.3: Compression ratio obtained compressing "paper1" for different self-compression options

difference is not very interesting in comparison with the whole time needed. Finally in Figure 5.3 we can see compression ratio achieved, where both self-compression versions performed about 5% better. According to worse compression ratios, more memory used and similar time needed we can rule out option *simple pruning only*.

We can not judge about single and multiple self-compression from just one file. The most interesting difference should be in compression ratios, so the tests were performed on Canterbury Corpus with $maxdepth = 40$ (Figure 5.4). Again compression ratios were practically the same, so we can choose *single self-compression* as the better one, because it needs less memory and time to achieve the same compression ratio.

5.3 Antidictionary Construction and Optimization

Another important part is to understand why is the DCA algorithm so greedy, when constructing suffix trie. In Figure 5.5 we can see how much nodes we create when building suffix trie and how their count decrease to almost negligible count, that we really use for compression. Number of nodes drops at most just after antidictionary construction and selection of only nodes leading to antiwords. Another reduction follows with self-compression and subsequent simple pruning. We can see, that both are quite effective.

In Figure 5.6 is this showed in more detail. Notice also the lowest node count plot representing *simple pruning only* option without *self-compression*. More nodes are pruned, because their gains are not improved using *self-compression*.

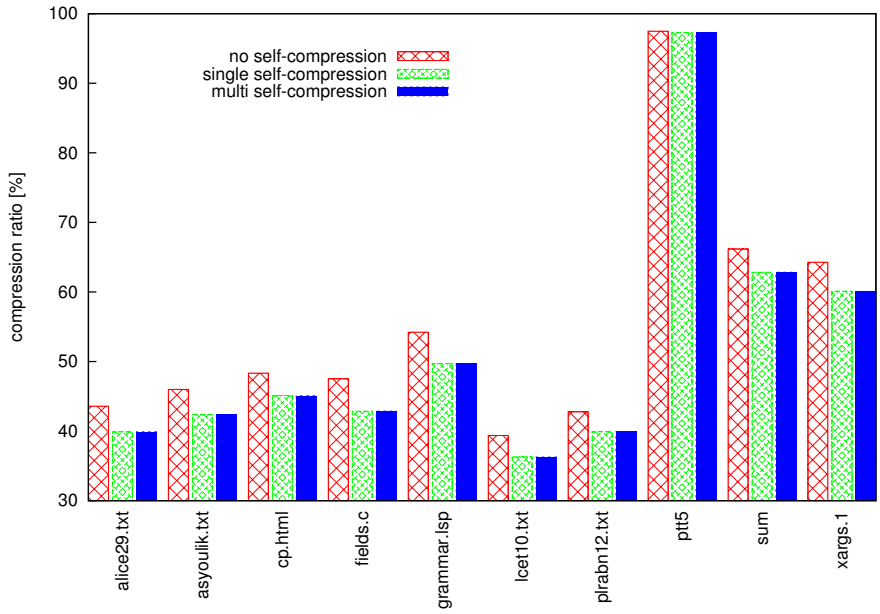

Figure 5.4: Compression ratios on Canterbury Corpus for different self-compression options

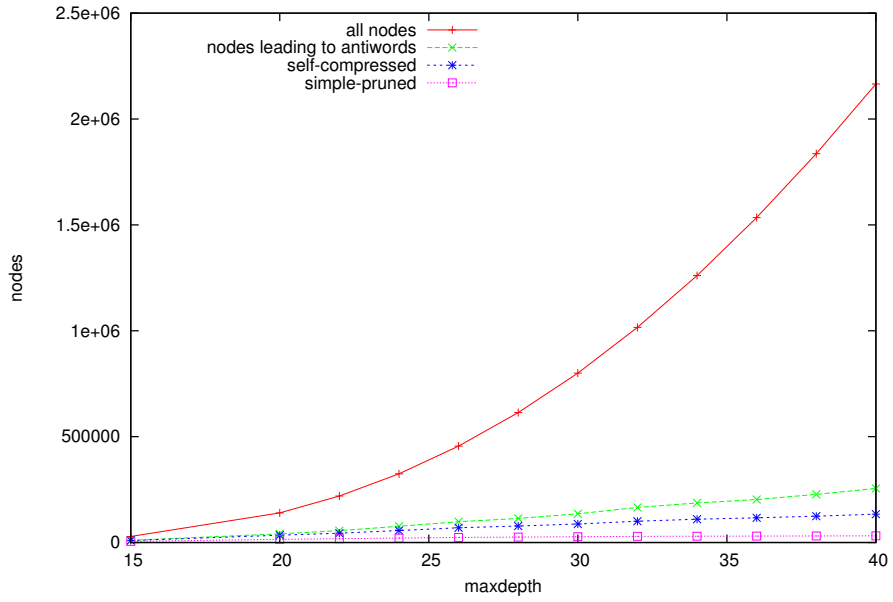

Figure 5.5: Number of nodes in relation to *maxdepth*

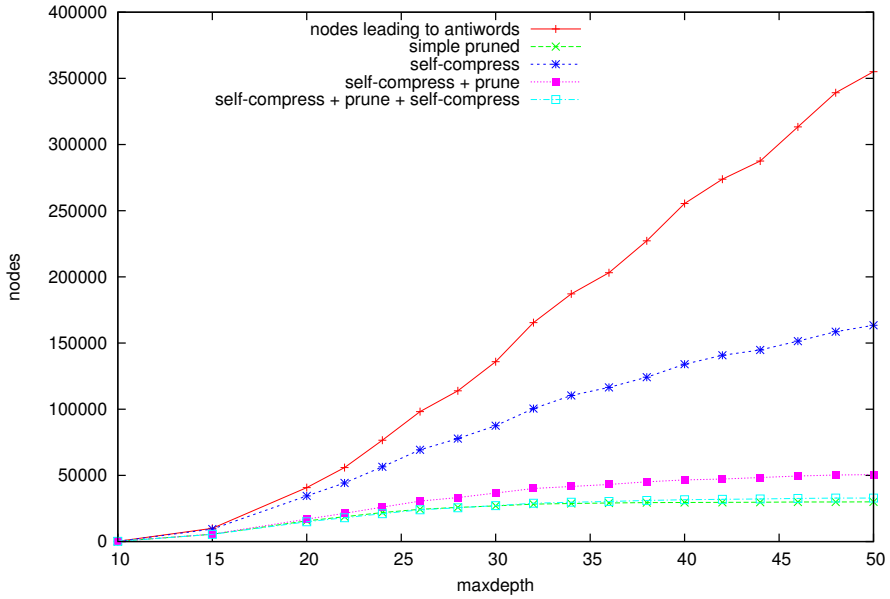

Figure 5.6: Number of nodes leading to antiwords in relation to *maxdepth*

Dependency of antiword count on *maxdepth* is shown in Figure 5.7 with lower part enlarged in Figure 5.8. You can notice a similarity between Figure 5.6 and Figure 5.7, which is caused by antiword count dependendency on node count. This relation can be more obvious from 5.9.

5.4 Data Compression

Now we are going to look at the more interesting part. Compression and decompression performance of static and dynamic compression scheme in relation to *maxdepth*. These results are again measured on "paper1" from Canterbury Corpus.

Figure 5.10 shows some expected behaviours of the implemented methods. Memory requirements are worst for static compression scheme using suffix trie, while dynamic compression scheme requires only about half of the memory. Suffix array static compression scheme's performance is definitely superior to both others, as its memory requirements almost don't grow with *maxdepth*. Also its initial requirements below *maxdepth*=25 are not very important, since below this value we don't get usable compression ratios. This is, what suffix array is really designed for.

However compression time is no longer so good for suffix array in Figure 5.11, still it outperforms suffix trie for $maxdepth > 25$. Dynamic compression scheme is much faster here, as it does not need to read text twice, do simple pruning and self-compression, compute gains or count visits, even to construct an antidictionary. It's much faster even for large *maxdepth* values.

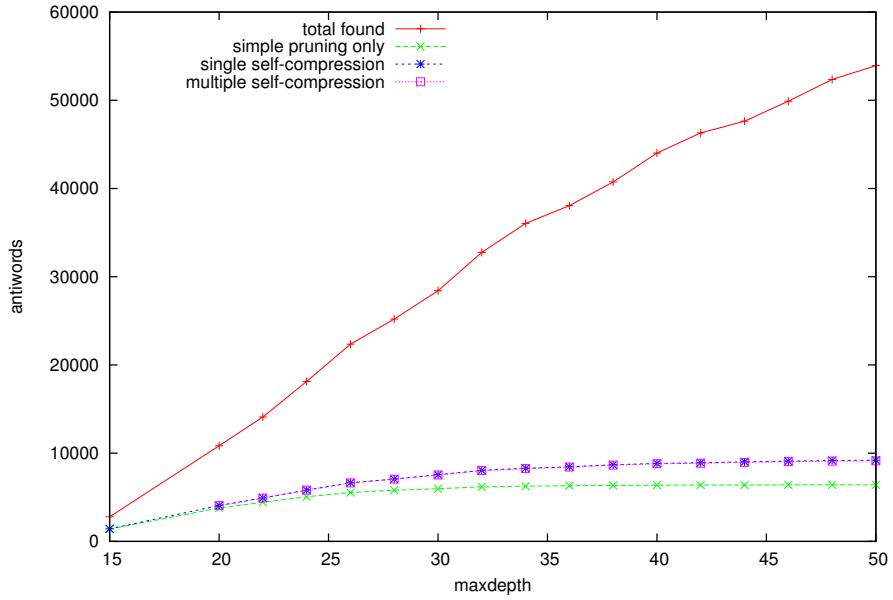

Figure 5.7: Number of antiwords in relation to *maxdepth*

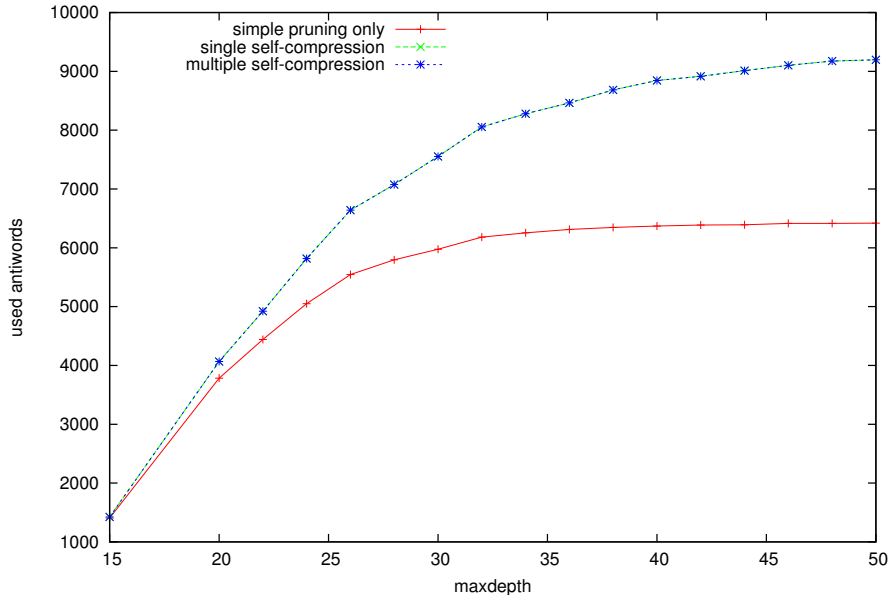

Figure 5.8: Number of used antiwords in relation to *maxdepth*

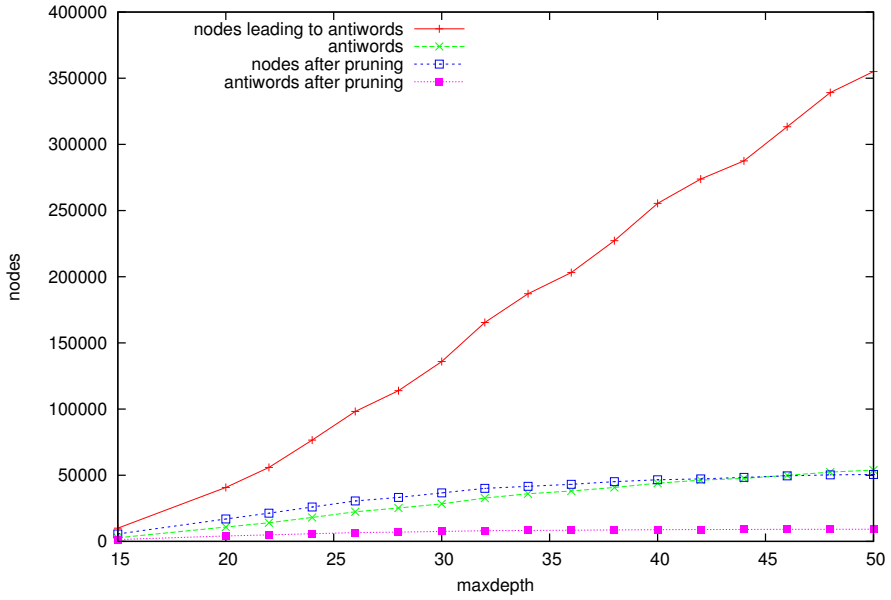

Figure 5.9: Relation between number of nodes and number of antiwords

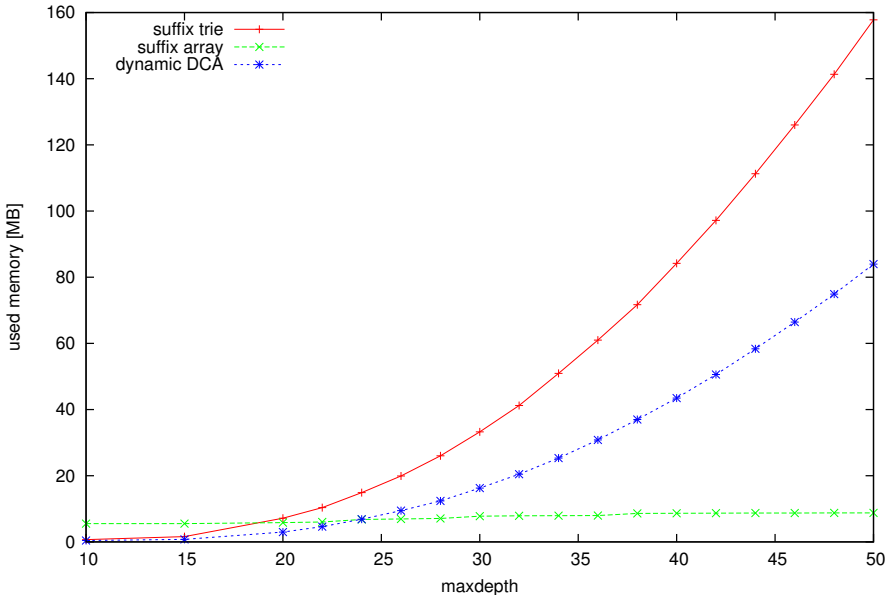

Figure 5.10: Memory requirements for compressing “paper1”

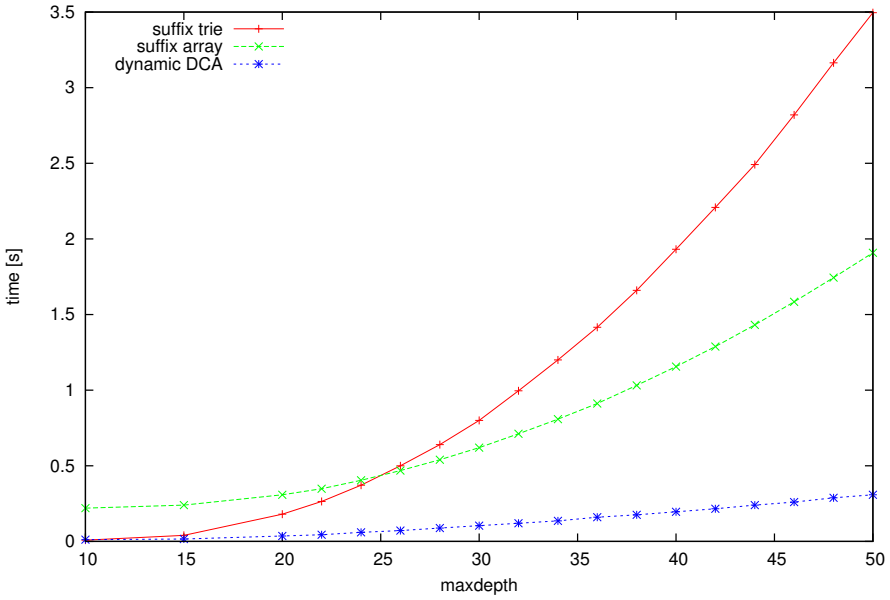

Figure 5.11: Time requirements for compressing “paper1”

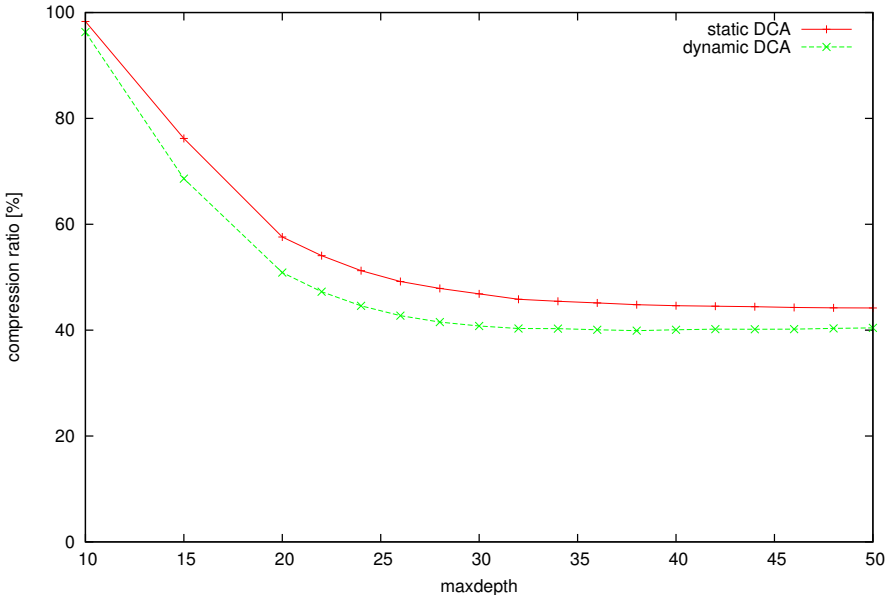

Figure 5.12: Compression ratio obtained compressing “paper1”

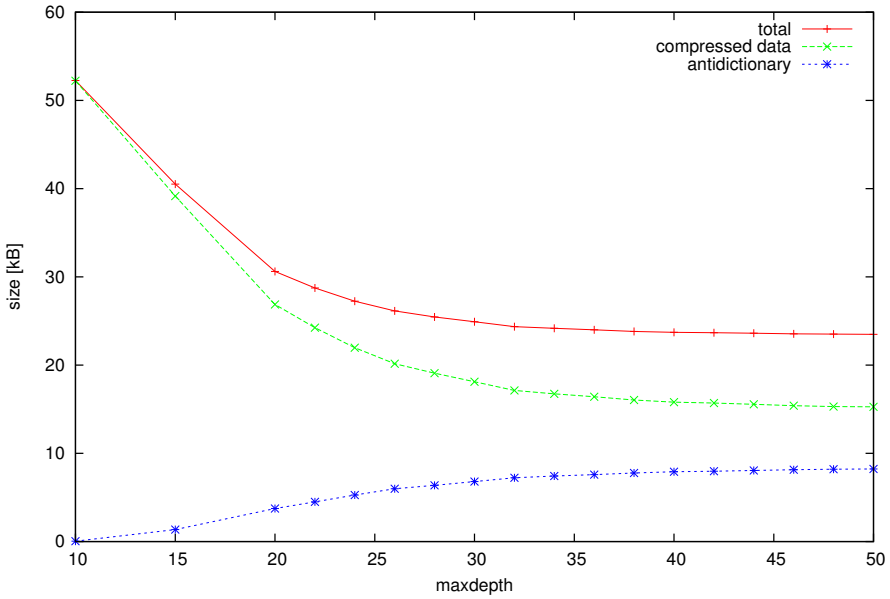

Figure 5.13: Compressed file structure created using static scheme compressing "paper1"

Another thing which playes for dynamic compression scheme is compression ratio (see Figure 5.12, utilizing its main advantage, not needing to store the antidictionary separately. But notice the algorithm's instability — whereas compression ratio of static compression scheme is improving for increasing *maxdepth*, compression ratio of dynamic DCA is floating for $maxdepth > 30$. This is caused by compressing more data, but at the same time getting more exceptions, which are expensive to code. Summarizing the results, dynamic compression scheme achieves about 5% better compression ratios than static compression scheme.

In Figure 5.13 we can see structure of the compressed file retrieved using static compression scheme. With growing *maxdepth* antidictionary size increases to shorten the compressed data, together we have got decreasing total file size.

5.5 Data Decompression

In turn in Figure 5.14 we can see that static compression scheme requires only a little amount of memory to decompress data, while dynamic compression scheme requires as much memory as during compression process. Smaller difference we can see in Figure 5.15 in time required to decompress file "paper1", static compression scheme is much faster again. Decompression speed and low memory requirements are an apparent advantage of static compression scheme.

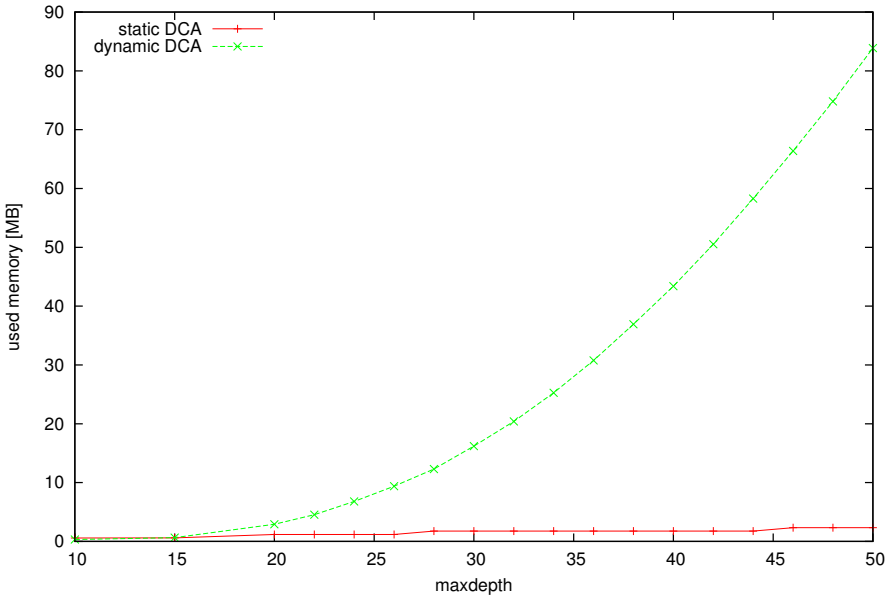

Figure 5.14: Memory requirements for decompressing “paper1.dz”

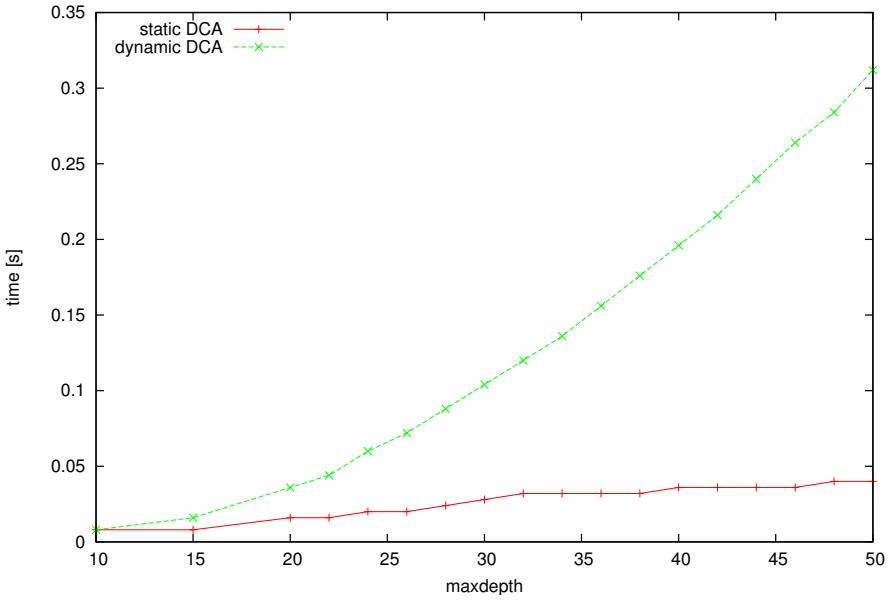

Figure 5.15: Time requirements for decompressing “paper1.dz”

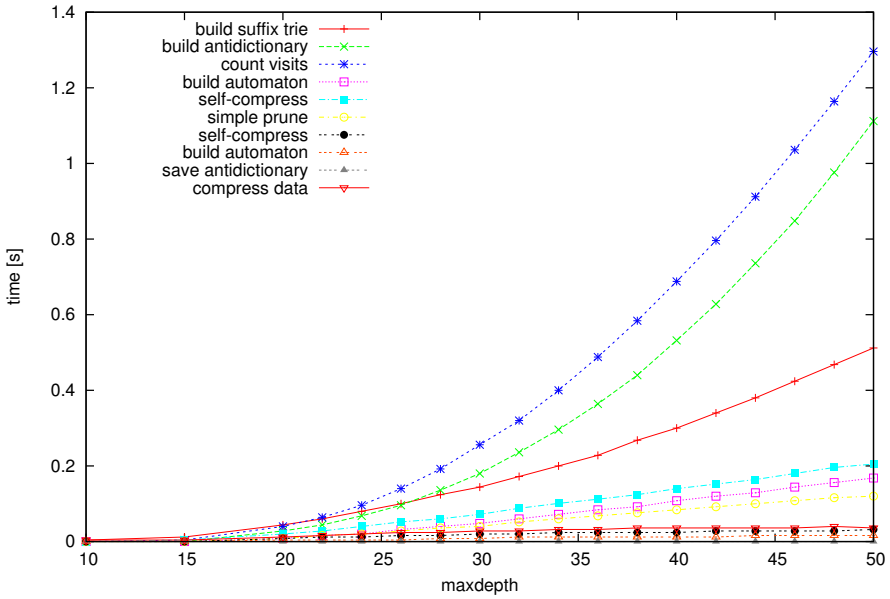

Figure 5.16: Time consumption of individual phases during compression process using suffix trie static compression scheme

5.6 Different Stages

For optimizing the implementation and for future research it is needed to know, how long each phase of the compression process lasts. This measurement was performed over "paper1" using suffix trie and suffix array. Graphs in Figure 5.16 illustrate time needed by each phase, graphs in Figure 5.17 display time contribution of each phase to the total compression time.

Looking at the graphs we can see, that building antidictionary and counting visits are the most expensive phases and their times are rising exponentially with *maxdepth*, while building suffix trie time rises only lineary.

Also looking at suffix array graphs (Figure 5.18 and Figure 5.19) we see constant complexity of building suffix array and least common prefix array, as they don't depend on *maxdepth*, while time of building antidictionary from suffix array rises exponentially. It looks like most efforts should be targeted on speeding up antidictionary construction whether using suffix trie or suffix array.

5.7 RLE

For experiments static and dynamic compression version with RLE (run length encoding) filter on input were also implemented. This filter compresses all "runs" of characters

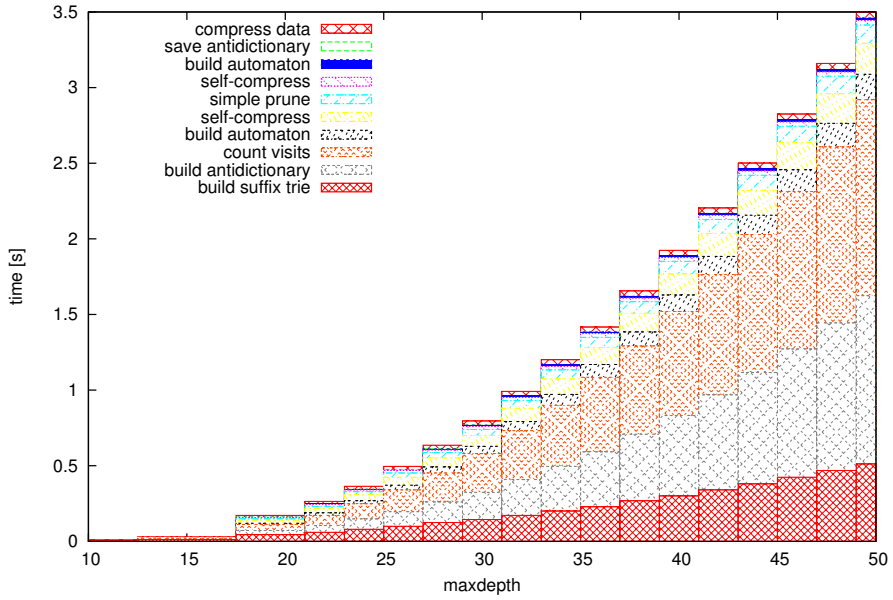

Figure 5.17: Suffix trie static compression scheme compression phases' contribution to total compression time

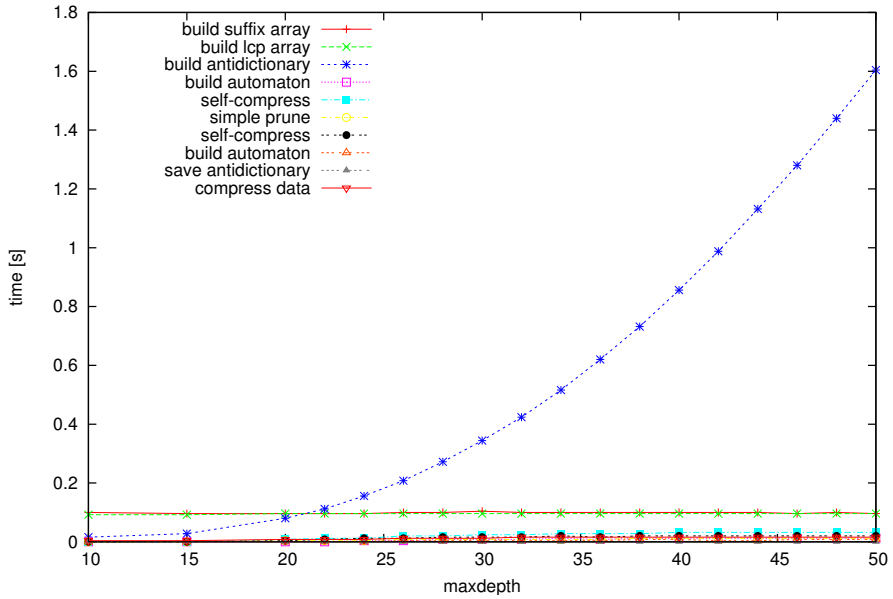

Figure 5.18: Time consumption of individual phases during compression process using suffix array static compression scheme

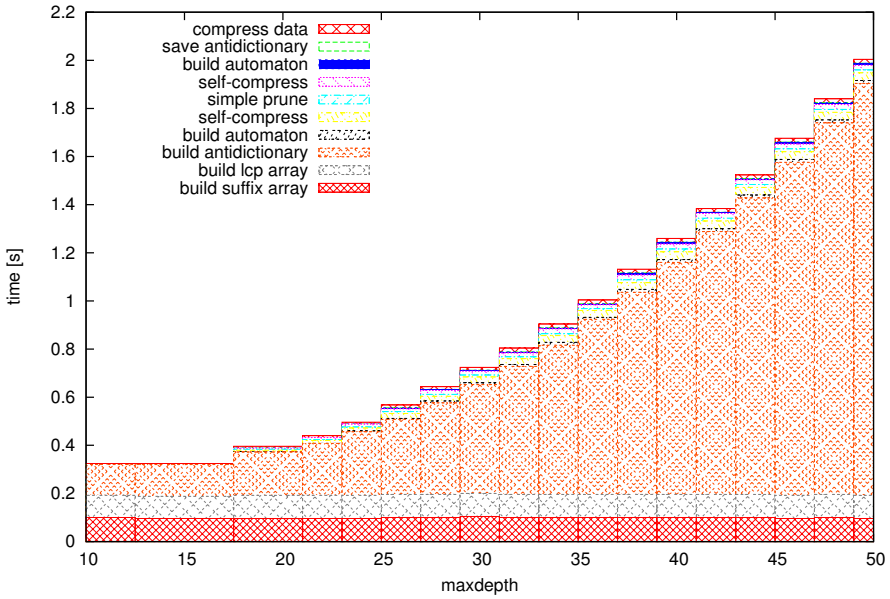

Figure 5.19: Suffix array static compression scheme compression phases' contribution to total compression time

longer than 3 and encodes the sequence length using Fibonacci coding [2]. Using of RLE has practically no influence to time or memory needed to compress a file, but it has significant impact to compressing particular files. Generally it slightly improves the compression ratio for smaller *maxdepth* values, but with larger *maxdepth* on the contrary it can make it slightly worse as in Figure 5.20. The main advantage comes with a particular type of files, where RLE improves compression ratio significantly as in Figure 5.21.

5.8 Almost Antiwords

For testing purposes almost antiwords implementation was developed using one pass heuristics based on suffix trie. As we can see in Figure 5.22 and Figure 5.23, for the same *maxdepth* value this method needs more time and memory due to more complicated antidictionary construction.

More interesting is compression ratio in Figure 5.24, where almost antiwords technique is better for smaller *maxdepth* values, but for $maxdepth > 30$ it is unable to improve compression ratio further. This implementation is not fine tuned and using multi-pass heuristics could lead to better values. In Figure 5.25 we can see structure of the compressed file, exceptions coding takes less space than antidictionary.

On many files almost antiwords technique surprisingly outperforms all the others (Figure 5.26) which makes this method very interesting for future experiments. For example

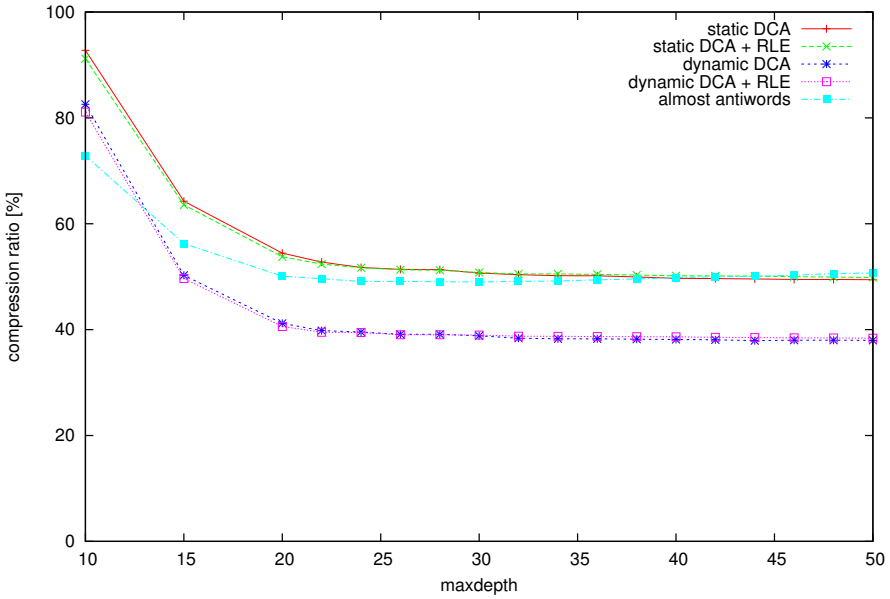

Figure 5.20: Compression ratio obtained compressing "grammar.lsp" from Canterbury Corpus

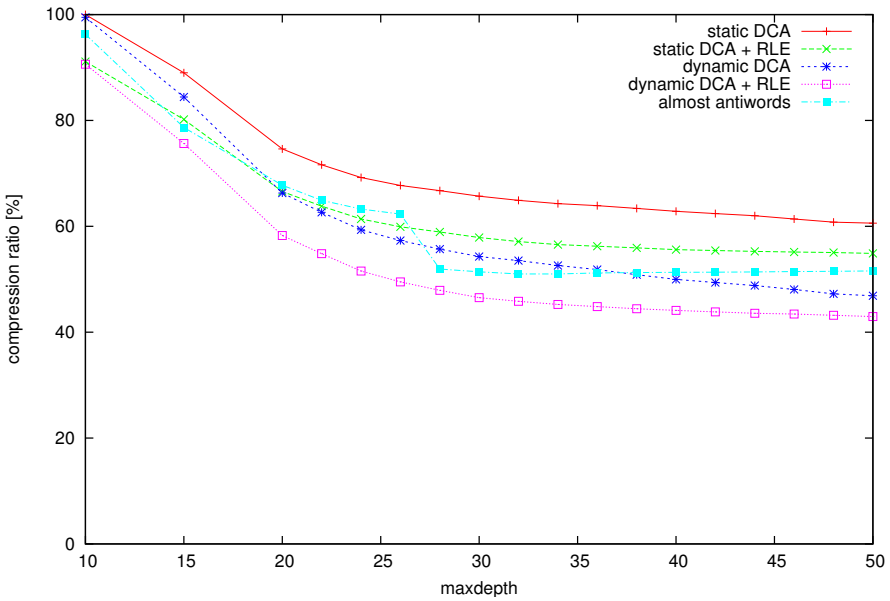

Figure 5.21: Compression ratio obtained compressing "sum" from Canterbury Corpus

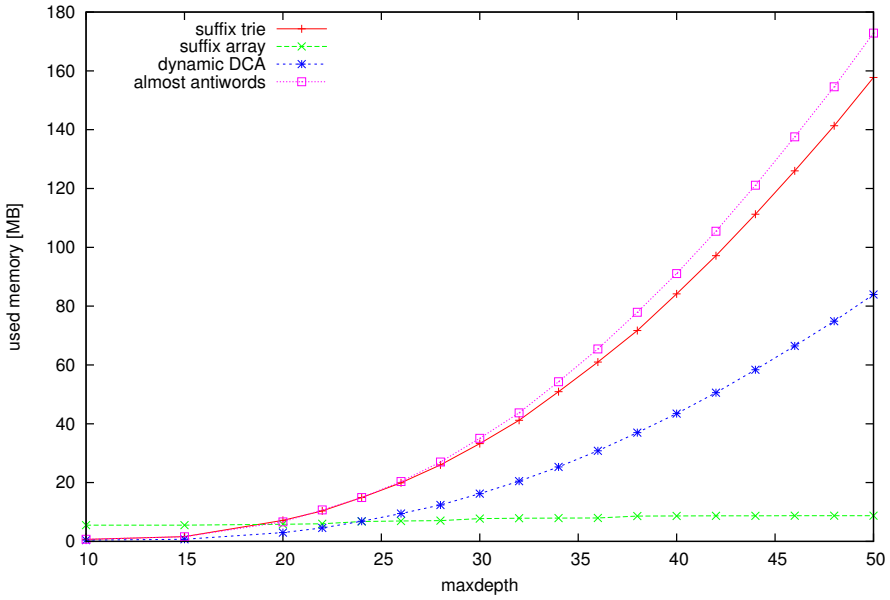

Figure 5.22: Memory requirements using almost antiwords

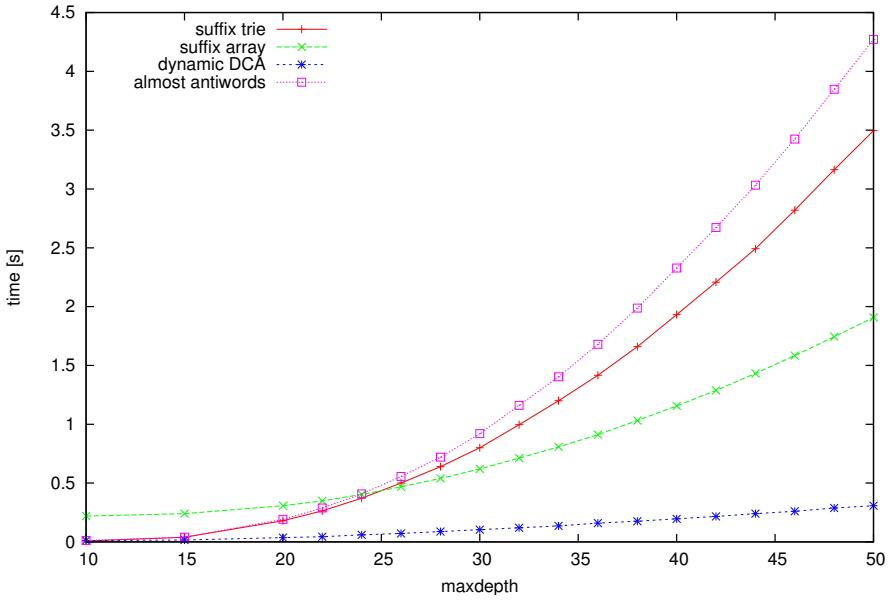

Figure 5.23: Time requirements using almost antiwords

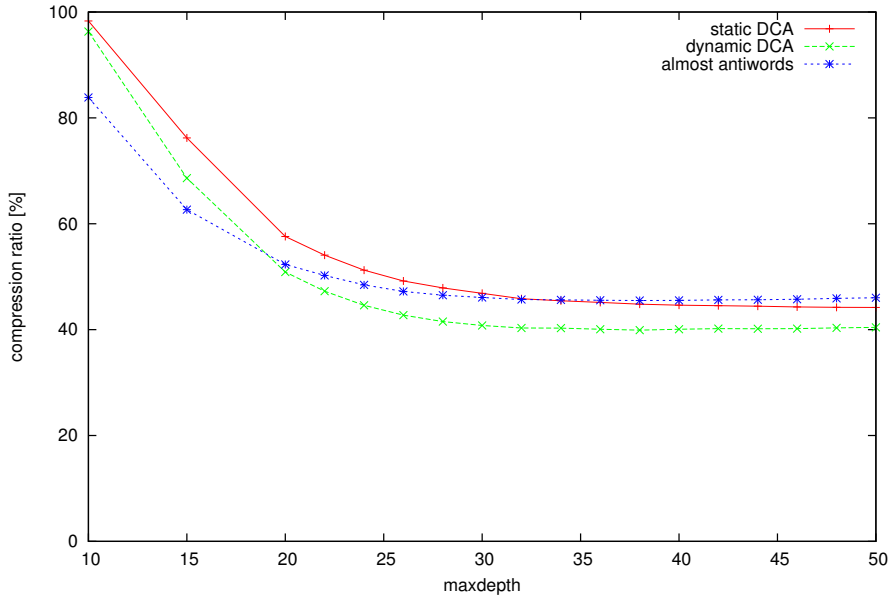

Figure 5.24: Compression ratio obtained compressing “paper1”

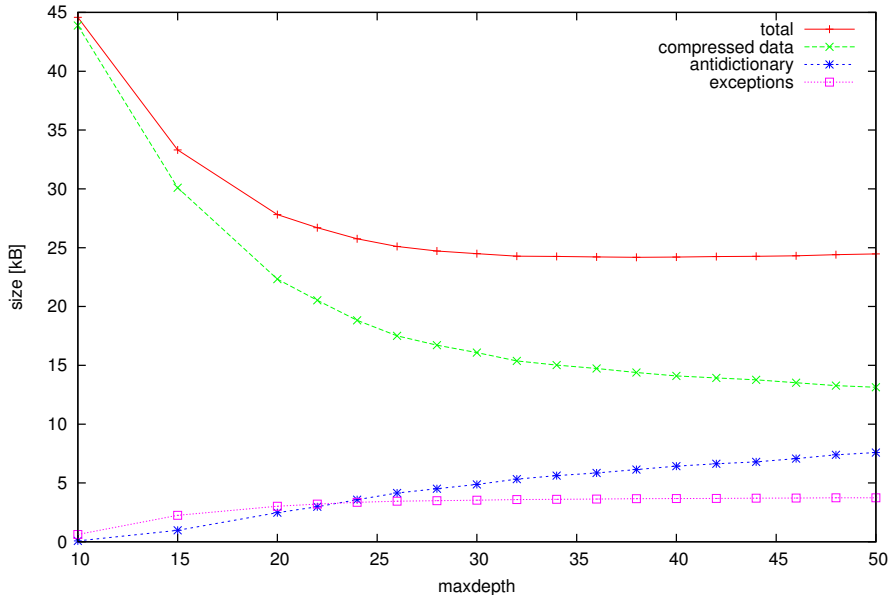

Figure 5.25: Compressed file structure created using almost antiwords compressing “paper1”

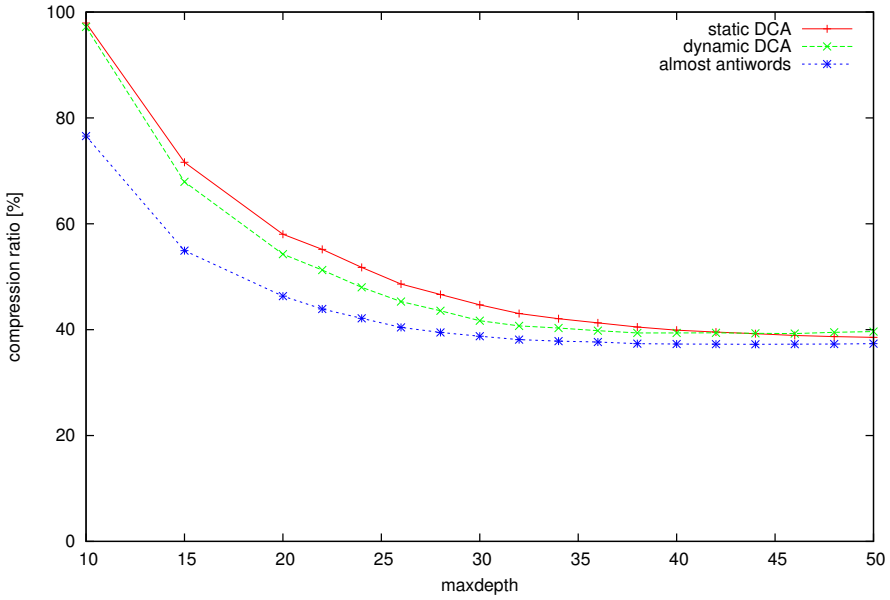

Figure 5.26: Compression ratio obtained compressing “alice29.txt”

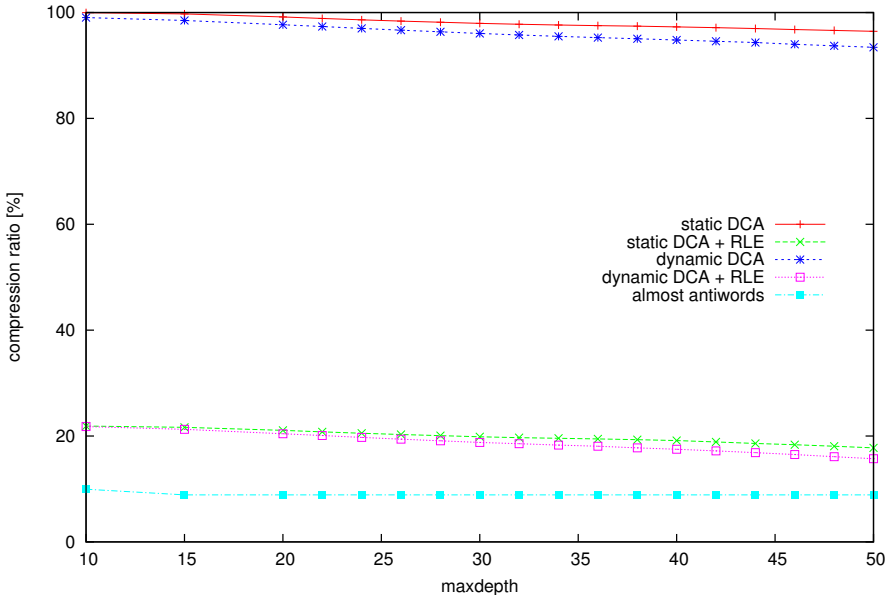

Figure 5.27: Compression ratio obtained compressing “ptt5”

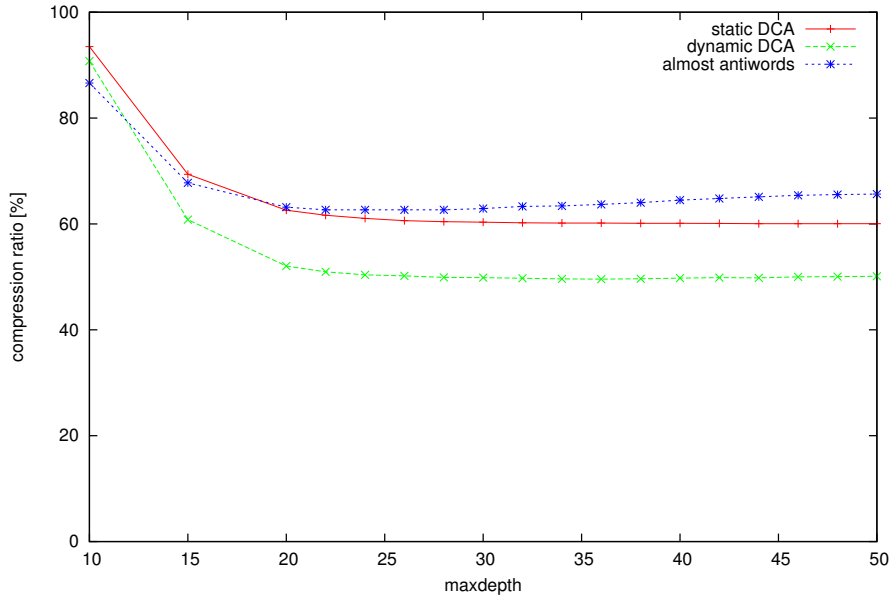

Figure 5.28: Compression ratio obtained compressing "xargs.1"

on "ptt5" file it gives better compression ratio than standard compression programs such as *gzip* or *bzip2* (Figure 5.27). However not everything is good using this technique, it looks like it has problem with small files and it is not stable, as it gets quickly to good compression ratio at *maxdepth* about 25, but then it is not able to improve the ratio further (Figure 5.28), it even gets worse compression ratios with increasing *maxdepth*. Most important on this method is, that we can get compression ratios similar to the ratios obtained by other compression schemes, but at lower *maxdepth*, requiring less memory.

5.9 Sliced Parallel Antidictionaries

This test is based on idea from Section 4.10. It was tested to compress bits from one byte separately using 8 parallel antidictionaries. The results for both static and dynamic compression scheme can be found in Tables 5.1 and 5.2. This measurement was performed on Canterbury Corpus with $maxdepth = 40$. Columns $b0 \ldots b7$ represent compression ratio obtained by compressing files created from the n-th bit of the original file only. Column *total* represents overall compression ratio obtained using parallel antidictionaries, column *orig* contains compression ratio obtained by not using parallel antidictionaries.

Static compression scheme using parallel antidictionaries reached much worse compression ratios in almost all cases. Dynamic compression scheme performed in a similar way with the exception for "ptt5" file, where it surprisingly obtained significantly better compression ratio. The experiment demonstrated, that there exists some type of files, where this method would be useful. Also compression the 7-th bit separately could lead

file	b0	b1	b2	b3	b4	b5	b6	b7	total	orig
alice29.txt	99.9	99.8	99.9	99.7	99.5	85.3	93.6	0.0	84.7	39.9
asyoulik.txt	99.9	99.5	99.9	99.8	99.5	85.7	94.6	0.0	84.9	42.4
cp.html	89.7	92.4	91.7	91.7	90.2	75.4	76.0	100.0	88.4	45.1
fields.c	99.3	98.3	98.4	98.8	94.7	78.3	88.5	0.1	82.1	42.9
grammar.lsp	100.2	96.3	100.0	99.6	97.4	73.8	89.5	0.2	82.3	49.7
lcet10.txt	99.0	98.9	99.2	99.1	99.0	89.1	91.5	0.0	84.5	36.3
plrabn12.txt	99.9	100.0	100.0	100.0	99.9	90.3	88.1	0.0	84.8	39.9
ptt5	91.1	91.5	91.2	91.3	93.2	93.3	93.3	92.9	92.2	97.3
sum	87.1	85.5	84.6	78.9	77.2	71.6	67.4	80.7	79.1	62.8
xargs.1	100.0	100.2	100.2	100.2	99.4	85.6	90.4	0.2	84.6	60.1

Table 5.1: Parallel antidictionaries using static compression scheme

file	b0	b1	b2	b3	b4	b5	b6	b7	total	orig
alice29.txt	124.8	120.1	127.8	122.2	108.7	73.2	104.3	0.0	97.6	39.4
asyoulik.txt	127.1	123.3	128.8	125.9	113.4	71.8	103.6	0.0	99.2	44.0
cp.html	95.8	99.1	99.0	100.0	93.5	61.8	75.1	2.3	78.3	39.0
fields.c	99.3	97.5	97.3	97.2	84.6	59.7	79.5	0.0	76.8	33.1
grammar.lsp	104.3	100.5	99.1	101.5	92.5	56.7	81.6	0.0	79.5	38.1
lcet10.txt	122.4	120.1	124.1	119.2	110.2	82.7	96.4	0.0	96.9	35.5
plrabn12.txt	128.2	125.0	130.6	126.2	113.4	83.1	101.4	0.0	101.0	41.5
ptt5	74.9	74.7	74.1	74.8	77.8	83.2	87.9	77.7	78.1	94.8
sum	66.7	68.7	68.1	62.2	61.7	57.6	51.6	76.9	64.2	50.0
xargs.1	118.8	118.9	117.8	119.5	110.8	64.7	93.9	0.0	93.0	49.8

Table 5.2: Parallel antidictionaries using dynamic compression scheme

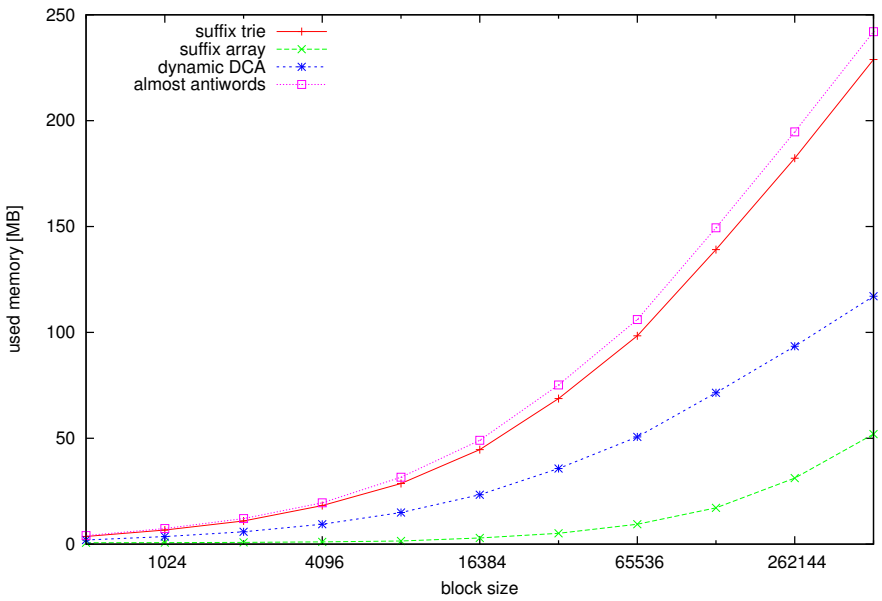

Figure 5.29: Memory requirements in relation to block size compressing “plrabn12.txt”

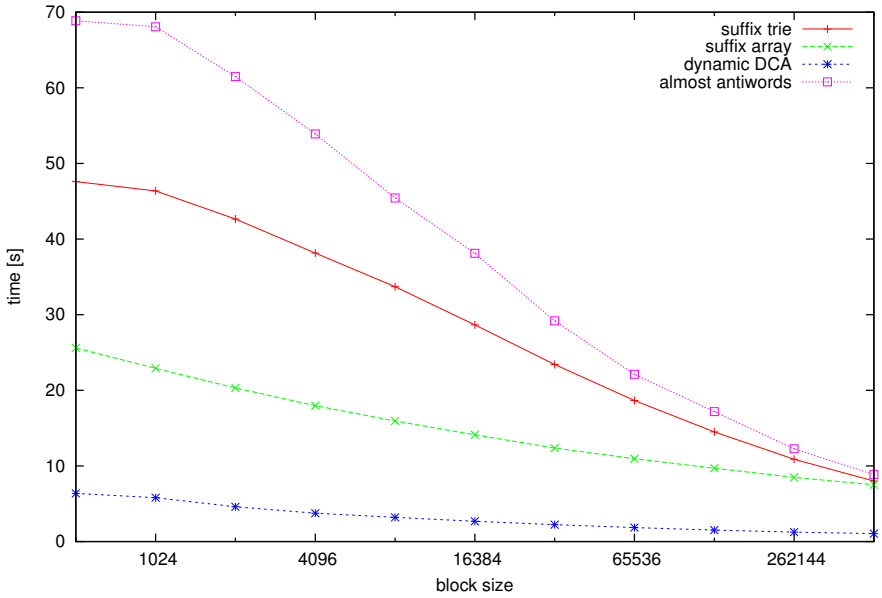

Figure 5.30: Time requirements in relation to block size compressing "plrabn12.txt"

to better compression ratios. However in general it can't be recommended.

5.10 Dividing Input Text into Smaller Blocks

Huge memory requirements of DCA method were already presented, that's why we can't build antidictionary over whole large files, but we should rather divide them into smaller blocks and compress them separately. Tests were made on "plrabn12.txt" file from Canterbury Corpus with $maxdepth = 40$, splitting the file into blocks of particular size and then compressing all these parts separately, summarizing the results.

Influence of block size on time and memory can be found in Figure 5.29 and Figure 5.30 respectively, but be careful, the x-axis is logarithmic. For suffix array memory requirements double with double file size, suffix trie and dynamic DCA need more memory but with higher block sizes their requirements grow slower. Considering time, larger files are better, as it is not needed to run some phases, such as building antidicionary, self-compression and simple pruning, more times. It looks that for files larger than 512kB suffix array will be the slowest, but for smaller files it is the fastest from static compression scheme methods.

Selected block size has a significant influence on compression ratio as shows Figure 5.31, this means we should use block as large as possible. A little surprise is improvement of almost antiwords's method with growing block size. In Figure 5.32 we see structure of the compressed file, with smaller blocks many information in antidictionaries are duplicated, that's why the antidictionary size is getting lower.

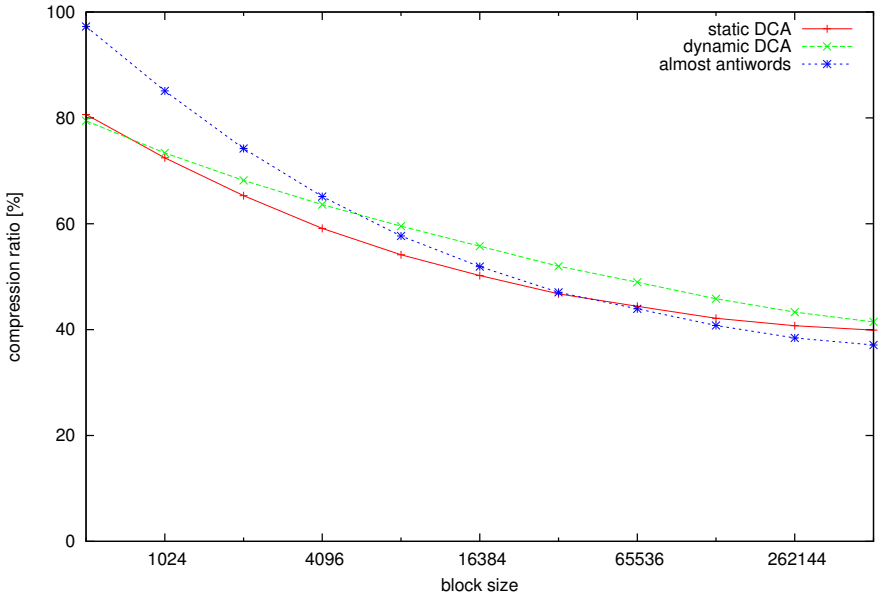

Figure 5.31: Compression ratio obtained compressing “plrabn12.txt”

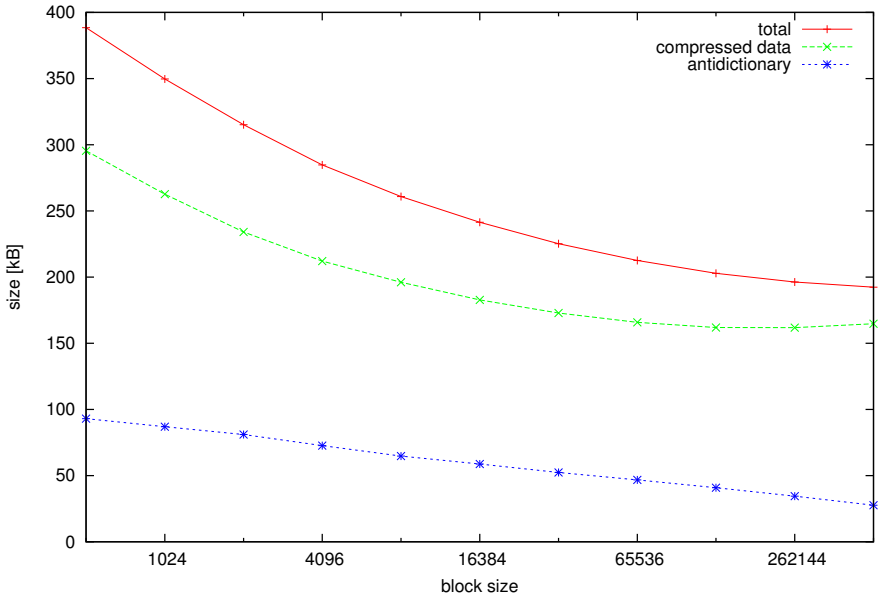

Figure 5.32: Compressed file structure created using static compression scheme in relation to block size compressing “plrabn12.txt”

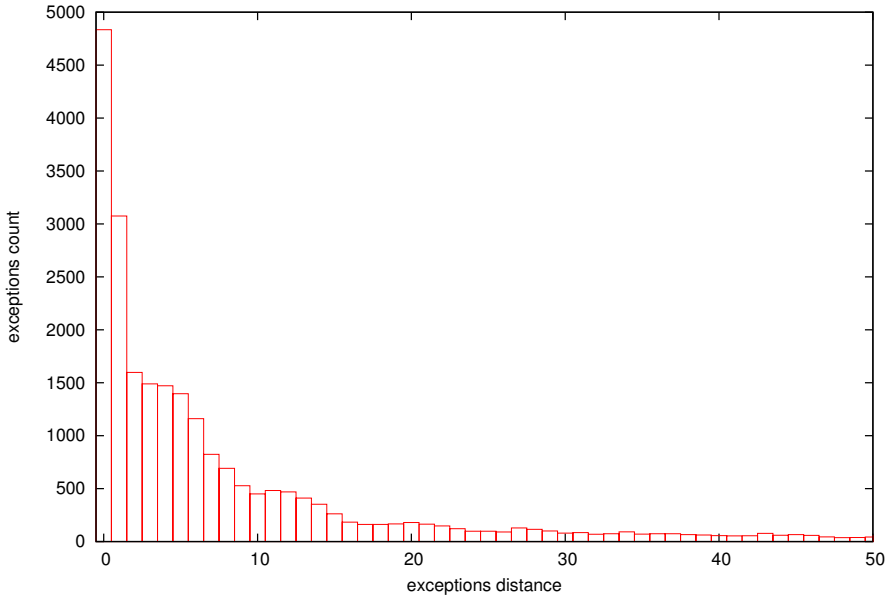

Figure 5.33: Dynamic compression scheme exception distances histogram

5.11 Dynamic Compression

In dynamic compression scheme we need to deal with exceptions, but before that we need to know something about them. Figure 5.33 is a histogram of exceptions distances for *maxdepth* = 40 compressing file "paper1" from Calgary Corpus. We can see, that most distances have value below 10. Fibonacci coding [2] was picked, but other universal coding or even Huffman coding could be useful, too. In Figure 5.34 we can see exception count in relation to *maxdepth*, which explains strange compression ratio dependency on *maxdepth* mentioned in Section 5.4. Generally dynamic compression scheme achieves good compression ratios, e.g. with "fields.c" (Figure 5.28), but sometimes things can go worse with increasing "maxdepth" like with "plrabn12.txt" in Figure 5.35.

5.12 Canterbury Corpus

All tests were run on the whole Canterbury Corpus and found the best compression ratios obtained by each compression method. They can be found in Table 5.3 and also in Figure 5.36. Static compression scheme stays in back, only with "plrabn10.txt" is better, while dynamic compression and almost antiwords alternately give the best compression ratios, but both have some odd behaviour on particular files.

Some interesting evaluation can be seen from graph averaging compression ratios over Canterbury Corpus in relation to *maxdepth* (Figure 5.37). Here looks dynamic compression scheme with RLE as the best followed by almost antifactors and later by static

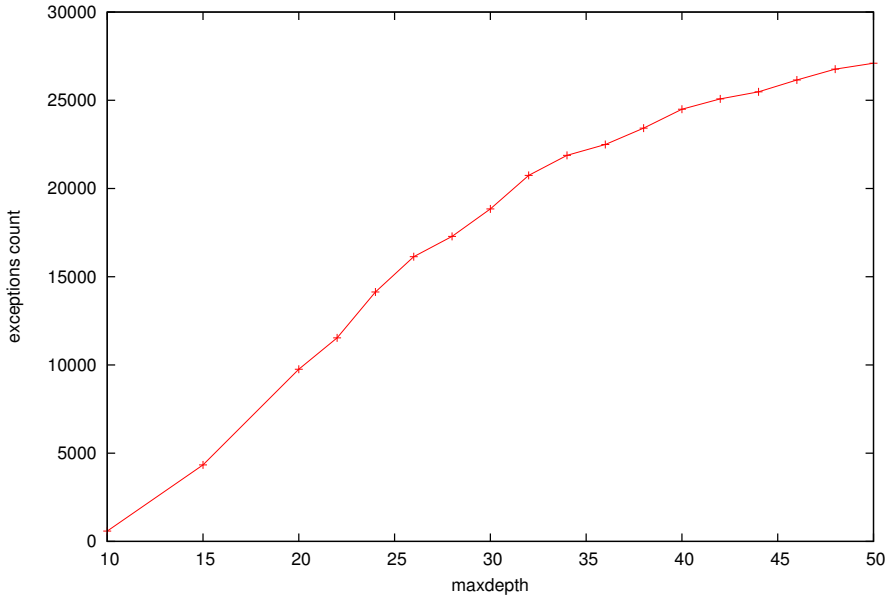

Figure 5.34: Exception count in relation to *maxdepth*

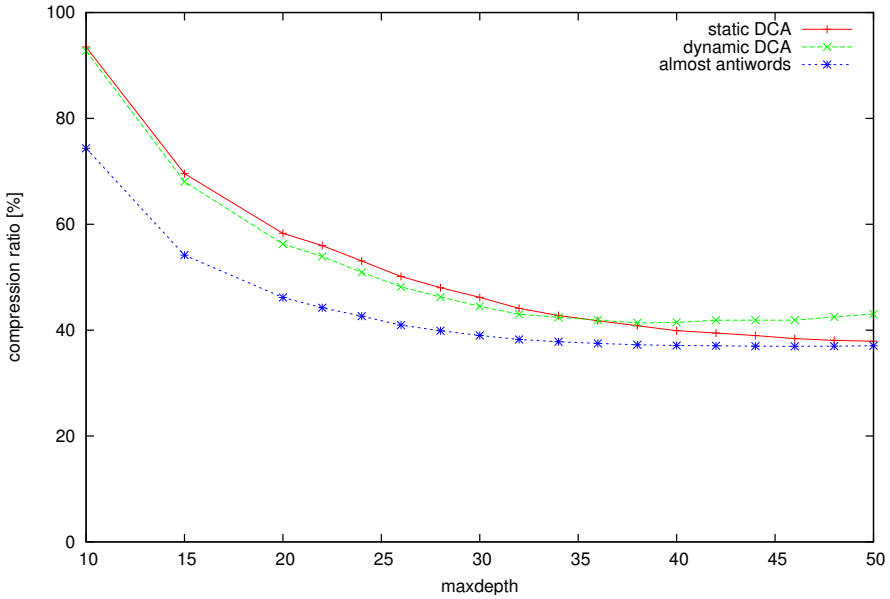

Figure 5.35: Compression ratio obtained compressing “plrabn12.txt”

method	almostaw	dynamic	dynamic-rle	static	static-rle
alice29.txt	**37.23**	39.25	38.95	38.90	38.54
asyoulik.txt	**41.19**	43.48	43.49	41.66	41.67
cp.html	44.37	**38.68**	38.83	44.69	44.81
fields.c	43.47	**32.84**	33.44	42.50	43.11
grammar.lsp	48.99	**37.92**	38.46	49.48	50.01
kennedy.xls	**25.04**	26.36	27.18	25.85	25.91
lcet10.txt	34.36	35.17	34.64	34.90	**34.30**
plrabn12.txt	**36.96**	41.37	41.34	38.40	38.39
ptt5	8.88	93.44	**16.49**	96.78	18.36
sum	51.01	46.88	**43.42**	61.39	55.15
xargs.1	62.67	**49.58**	**49.58**	60.04	60.04

Table 5.3: Best compression ratios obtained on Canterbury Corpus

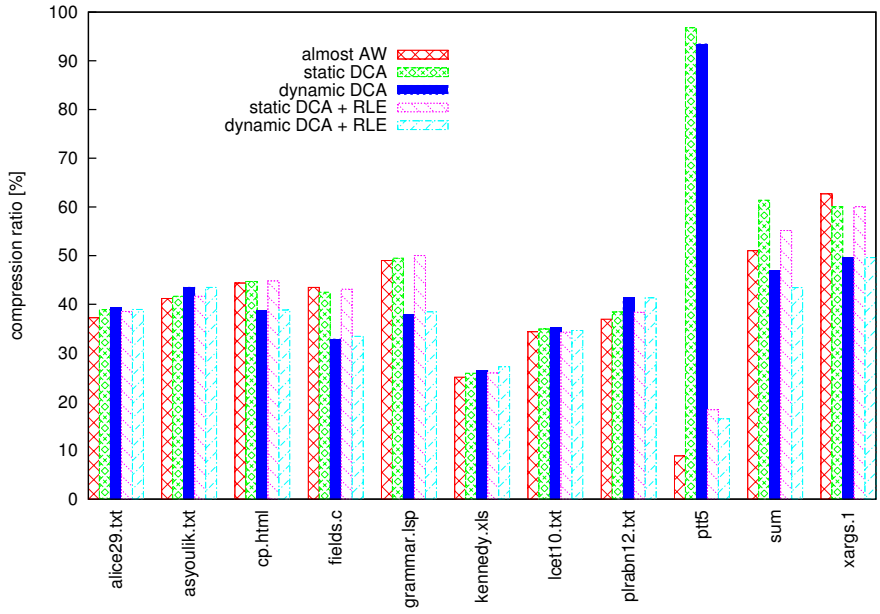

Figure 5.36: Best compression ratio obtained by each method on Canterbury Corpus

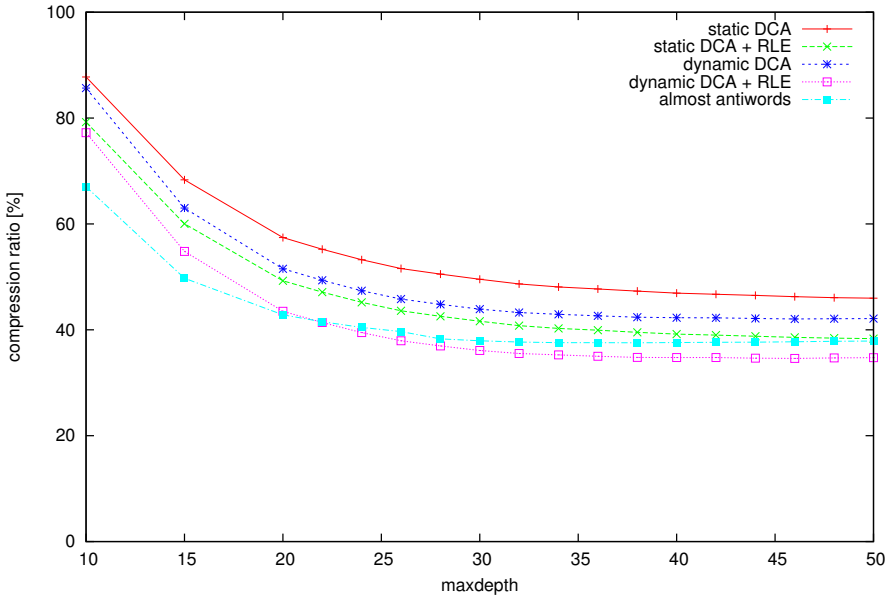

Figure 5.37: Average compression ratio obtained by each method on Canterbury Corpus

compression scheme with RLE. Another interesting evaluation are average compression speed and time (input characters compressed per second) in Figure 5.38 and in Figure 5.39. What we are also interested in is memory needed to compress 1 byte of input text in Figure 5.40.

5.13 Selected Parameters

Results on Canterbury Corpus were analyzed and all is prepared for the final test. The smallest memory and time requirements were claimed while still obtaining reasonable compression ratios. For each method appropriate *maxdepth* k were selected and compared their results are to be compared. The selection follows:

- almost antiwords, $k = 30$
- dynamic DCA + RLE, $k = 32$
- static DCA + RLE, $k = 30$ (suffix trie/suffix array)
- static DCA + RLE, $k = 34$ (suffix trie/suffix array)
- static DCA + RLE, $k = 40$ (suffix trie/suffix array)

From the results presented in Figures 5.41, 5.42 and 5.43 we can make some conclusions. Exact values obtained can be found in Table 5.4.

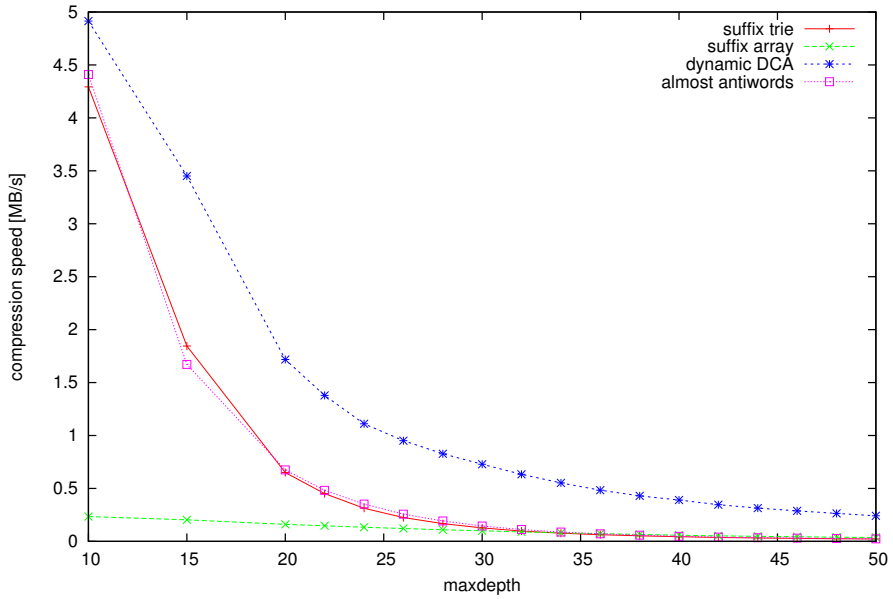

Figure 5.38: Average compression speed (compressed characters per second) of each method on Canterbury Corpus

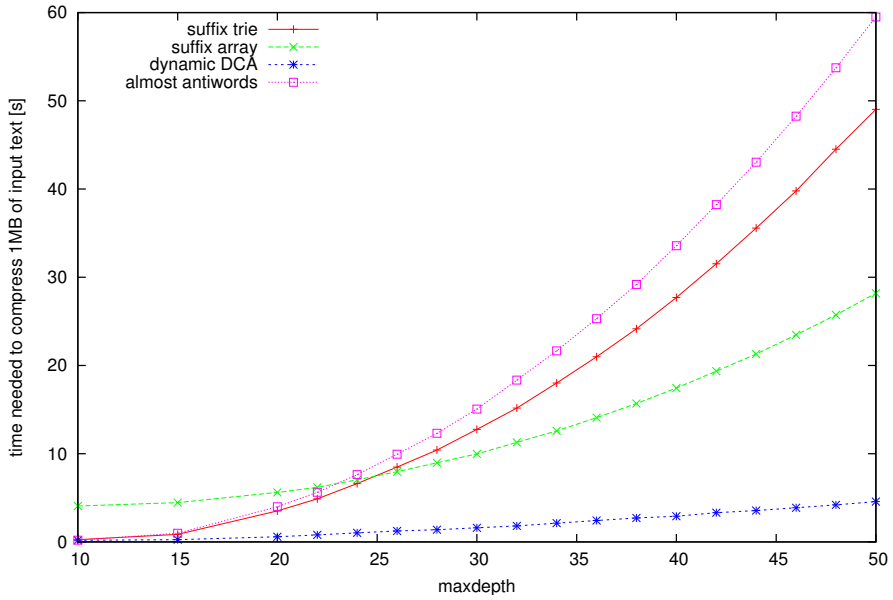

Figure 5.39: Average time needed to compress 1MB of input text on Canterbury Corpus

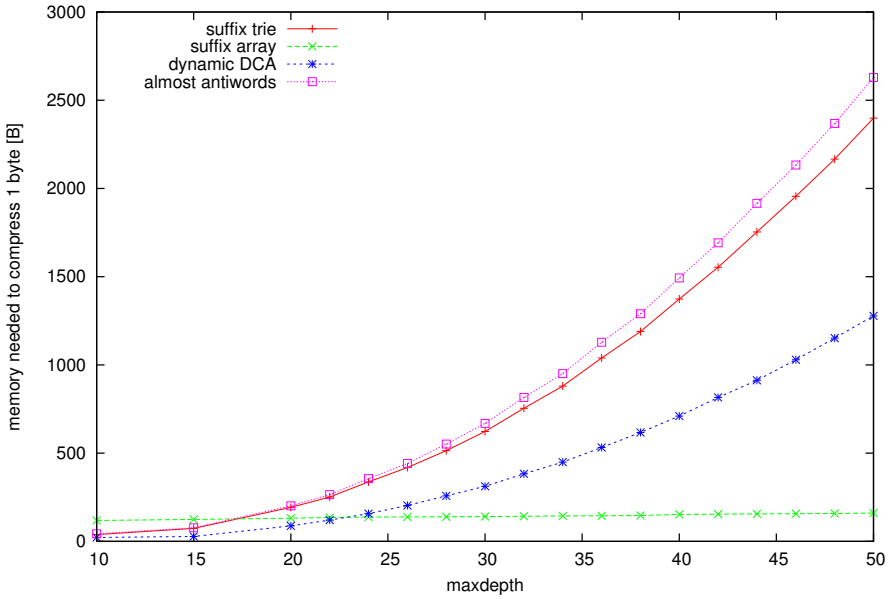

Figure 5.40: Memory needed in average by each method to compress 1 byte of input text on Canterbury Corpus

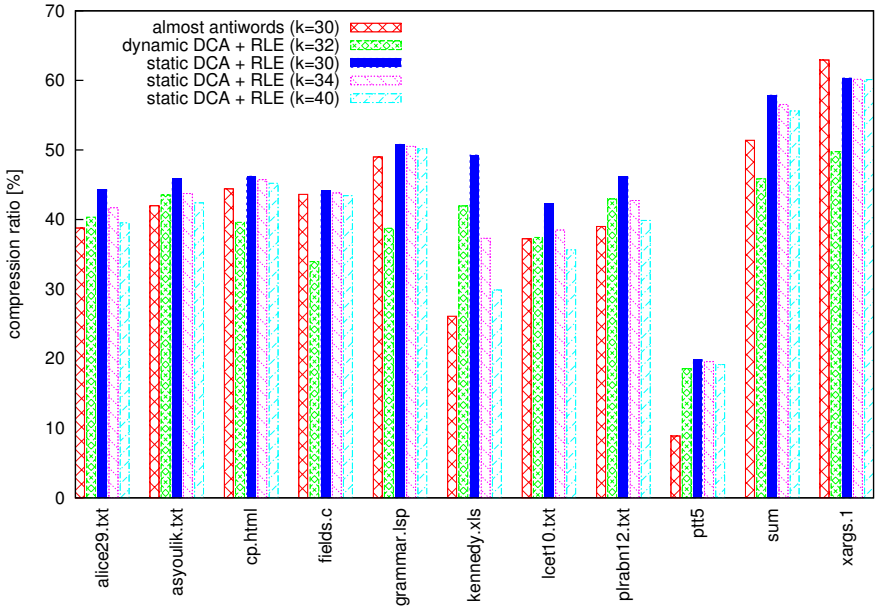

Figure 5.41: Compression ratio obtained by selected methods on Canterbury Corpus

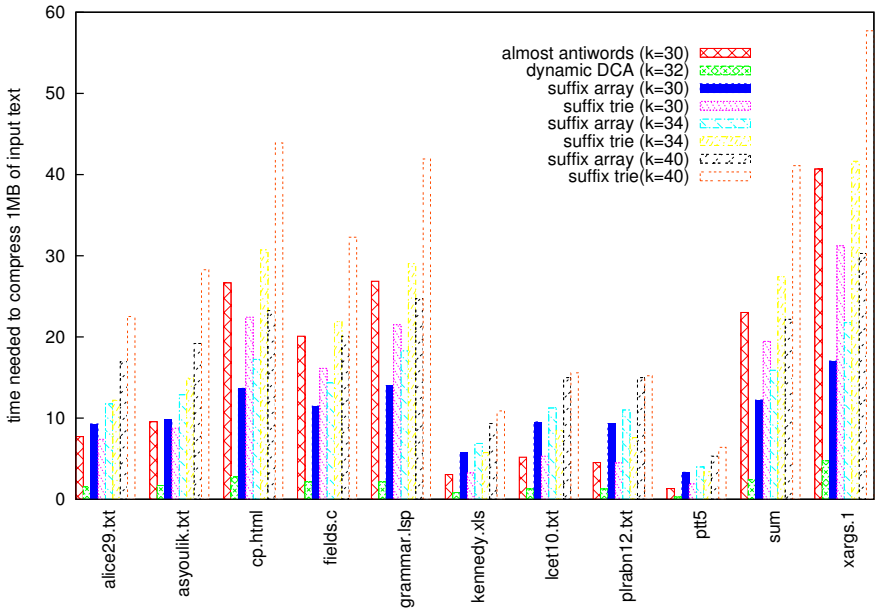

Figure 5.42: Time needed to compress 1MB of input text

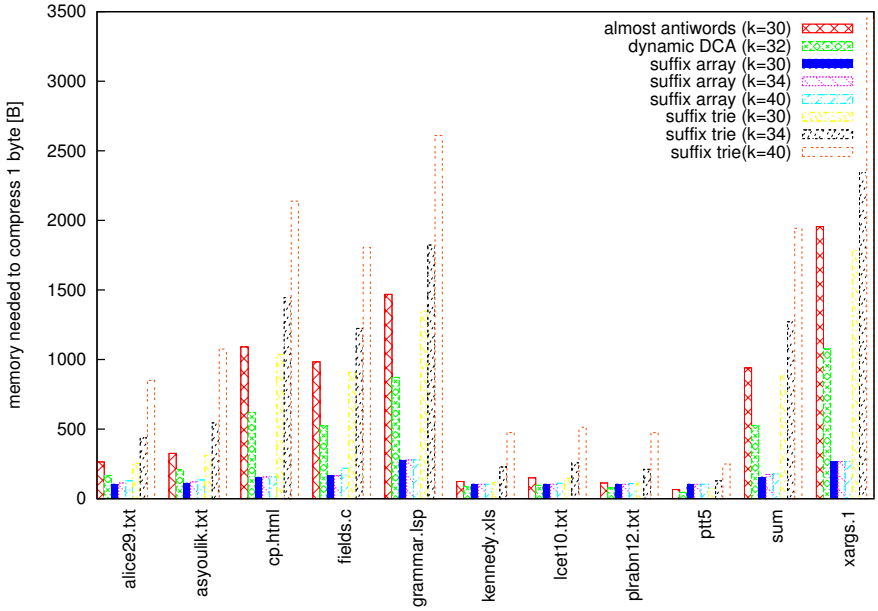

Figure 5.43: Memory needed by selected methods to compress 1 byte of input text on Canterbury Corpus

file	original	gzip	bzip2	almostaw-30	dynamic-rle-32	rle-34
alice29.txt	152089	54423	**43202**	58965	61365	63386
asyoulik.txt	125179	48938	**39569**	52550	54462	54756
cp.html	24603	7991	**7624**	10927	9743	11250
fields.c	11150	3134	**3039**	4865	3784	4885
grammar.lsp	3721	**1234**	1283	1823	1441	1880
kennedy.xls	1029744	206767	**130280**	268827	431929	384241
lcet10.txt	426754	144874	**107706**	158887	159724	164221
plrabn12.txt	481861	195195	**145577**	187914	207005	205967
ptt5	513216	56438	49759	**45556**	95175	100432
sum	38240	12920	**12909**	19655	17527	21619
xargs.1	4227	**1748**	1762	2659	2102	2543

Table 5.4: Compressed file sizes obtained on Canterbury Corpus

file	original	gzip	bzip2	almostaw-30	dynamic-rle-32	rle-34
bib	111261	35059	**27467**	40247	38078	41177
book1	768771	313370	**232598**	306609	360005	363396
book2	610856	206681	**157443**	237339	242923	253609
geo	102400	68489	**56921**	77219	88801	78570
news	377109	144835	**118600**	173141	164269	180022
obj1	21504	**10318**	10787	16154	13160	14544
obj2	246814	81626	**76441**	132067	108350	130868
paper1	53161	18570	**16558**	24496	21408	24146
paper2	82199	29746	**25041**	33499	34076	35792
pic	513216	56438	49759	**45556**	95175	100432
progc	39611	13269	**12544**	18602	15961	18496
progl	71646	16267	**15579**	24898	21711	25339
progp	49379	11240	**10710**	18670	14157	17256
trans	93695	18979	**17899**	34159	24166	32223

Table 5.5: Compressed file sizes obtained on Calgary Corpus

Method	Advantages	Disadvantages
almost antiwords	good compression ratios, decompression speed	hard implementation, compression speed and memory requirements, algorithm instability
static DCA	memory requirements (when using suffix array), decompression speed, compressed pattern matching	compression speed, slightly worse compression ratios
dynamic DCA	good compression ratios, fast compression speed, compression memory requirements	slow decompression and decompression memory requirements

Table 5.6: Pros and cons of different methods

If we have only little amount of memory, antidictionary construction using suffix array would be the right choice. When we are not interested in low decompression time, dynamic DCA gives us the best performance. If we are interested in compression ratio, we can choose from almost antiwords or dynamic DCA. Methods overview is presented in Table 5.6, algorithm instability means, that it does not give better compression ratio with increasing k.

Looking at static compression performance, *maxdepth* $k = 34$ looks the best, it gives better compression ratio than for $k = 30$ comparable to ratios obtained using almost antiwords or dynamic DCA, also it runs in much shorter time than for $k = 40$. Using suffix array for antidictionary construction is generally a good idea, not only considering memory requirements but it is also faster at $k = 34$ than antidictionary construction using suffix trie.

5.14 Calgary Corpus

Results for Calgary Corpus are presented, too, as it is still broadly used for evaluating compression methods, see Table 5.5.

Chapter 6

Conclusion and Future Work

6.1 Summary of Results

In this thesis data compression using antidictionaries with different techniques was implemented and their performance on standard sets of files for evaluating compression methods were presented. This work extends research of Crochemore, Mignosi, Restivo, Navarro and others [6, 7], who introduced the original idea of data compression using antidictionaries, described the static compression scheme thoroughly with antidictionary construction using suffix trie and also introduced almost antifactors improvement. This thesis has introduced antidictionary building using suffix array structure instead of suffix trie, also dynamic compression scheme was explained and some suggestions of how to improve compression ratios and how to solve huge memory requirements were provided.

Several data compression using antidictionaries methods were implemented — static compression scheme using suffix trie or suffix array for antidictionary construction, dynamic compression scheme using suffix trie and static compression scheme with almost antiwords using suffix trie. Their results compressing files from Canterbury and Calgary corpuses were evaluated.

It turned out that one of the biggest problems concerning data compression using antidictionaries is actually building the antidictionary, it requires not only much time but even much memory. Using suffix array for antidictionary lowers memory requirements significantly. As the antidictionary is usually built over the whole input file, it is a good idea to restrict block length processed in one round and to split the file into more blocks using different antidictionaries. This limit depends on the memory available, as larger blocks mean better compression ratio and lower the time requirements.

The most important parameter of all considered methods is *maxdepth* k limiting the length of antiwords. A suitable value of this parameter was selected for each method. For static compression scheme an idea of representing antidictionary by text generating it is introduced, which could improve compression ratio by reducing space needed for antidictionary representation.

Another improvement is to use RLE (run length encoding) as an input filter to hide static and dynamic compression scheme inability of compressing strings of form 0^n1, respectively their repetitions in case of dynamic compression scheme. According to the experiments methods equipped with RLE performed better.

It is not possible to pick the best method for everything, different usage scenarios have to be considered. If we need fast decompression speed, we can use static compression scheme or almost antiwords, dynamic compression scheme is not appropriate as its time and memory requirements for decompressing text are the same as when compressing. Nevertheless dynamic compression scheme could be useful for its best compression speed, good compression ratios and easy implementation.

Somewhat different it is when we need fast compressed pattern matching, then currently we have only choice of static compression scheme. If we have only little amount of memory available, static compression scheme with suffix array construction has the least memory requirements. And finally for best compression ratios we can choose from almost antifactors or dynamic compression scheme equipped with RLE in dependence to our decompression speed demands.

Based on the measurements some candidates were selected and compared with standard compression programs "gzip" and "bzip2". DCA showed, that on particular files it could be a good competitor to them, but still with much larger resources requirements. However DCA is an interesting compression method using current theories about finite automata and data structures for representing all text factors. Its potential could be in the compressed pattern matching abilities.

6.2 Suggestions for Future Research

Almost antiwords technique performed surprisingly well even using one-pass heuristics, but its time and memory requirements for building antidictionary from suffix trie were too greedy. More research could be done to reduce them as well as in compressed pattern matching in texts compressed using almost antiwords.

Another possible improvement concerns static compression scheme, where representing the antidictionary by text generating it seems promising, improving the compression ratio. In the considered methods Fibonacci code was used for storing exception distances or lengths of runs in RLE, but may be some more optimal code could be used.

The suffix array construction is using modified Manzini-Ferragina implementation for sorting text with binary alphabet, whereas it was originally developed for larger alphabets, which means that the used suffix array and lcp array construction may be not optimal.

Finally some more work could be done on optimizing the codes, as they were developed rather for testing and research purposes with many customizable parameters than for good performance.

Bibliography

[1] A. V. Aho and M. J. Corasick. Efficient string matching: An aid to bibliographic search. *Commun. ACM*, 18(6):333–340, 1975.

[2] A. Apostolico and A. S. Fraenkel. Robust transmission of unbounded strings using fibonacci representations. *IEEE Transactions on Information Theory*, 33(2):238–245, 1987.

[3] M.-P. Béal, F. Mignosi, and A. Restivo. Minimal forbidden words and symbolic dynamics. In C. Puech and R. Reischuk, editors, *STACS*, volume 1046 of *Lecture Notes in Computer Science*, pages 555–566. Springer, 1996.

[4] T. C. Bell, I. H. Witten, and J. G. Cleary. Modeling for text compression. *Computer Science Technical Reports*, pages 327–339, 1988.

[5] M. Burrows and D. Wheeler. A block-sorting lossless data compression algorithm. *SRC Research Report 124, Digital Equipment Corporation*, 1994.

[6] M. Crochemore, F. Mignosi, A. Restivo, and S. Salemi. Text compression using antidictionaries. In J. Wiedermann, P. van Emde Boas, and M. Nielsen, editors, *ICALP*, volume 1644 of *Lecture Notes in Computer Science*, pages 261–270. Springer, 1999.

[7] M. Crochemore and G. Navarro. Improved antidictionary based compression. In *SCCC*, pages 7–13. IEEE Computer Society, 2002.

[8] M. Davidson and L. Ilie. Fast data compression with antidictionaries. *Fundam. Inform.*, 64(1-4):119–134, 2005.

[9] R. Grossi and J. S. Vitter. Compressed suffix arrays and suffix trees with applications to text indexing and string matching. *SIAM J. Comput.*, 35(2):378–407, 2005.

[10] IEEE Computer Society. *2005 Data Compression Conference (DCC 2005), 29-31 March 2005, Snowbird, UT, USA*. IEEE Computer Society, 2005.

[11] S. Kurtz. Reducing the space requirement of suffix trees. *Softw., Pract. Exper.*, 29(13):1149–1171, 1999.

[12] U. Manber and G. Myers. Suffix arrays: A new method for on-line string searches. In *SODA*, pages 319–327, 1990.

[13] G. Manzini and P. Ferragina. Engineering a lightweight suffix array construction algorithm. In R. H. Möhring and R. Raman, editors, *ESA*, volume 2461 of *Lecture Notes in Computer Science*, pages 698–710. Springer, 2002.

[14] H. Morita and T. Ota. A tight upper bound on the size of the antidictionary of a binary string. In C. Martínez, editor, *2005 International Conference on Analysis of Algorithms*, volume AD of *DMTCS Proceedings*, pages 393–398. Discrete Mathematics and Theoretical Computer Science, 2005.

[15] M. Powell. Evaluating lossless compression methods, 2001.

[16] S. J. Puglisi, W. F. Smyth, and A. Turpin. The performance of linear time suffix sorting algorithms. In *DCC* [10], pages 358–367.

[17] Y. Shibata, M. Takeda, A. Shinohara, and S. Arikawa. Pattern matching in text compressed by using antidictionaries. In M. Crochemore and M. Paterson, editors, *CPM*, volume 1645 of *Lecture Notes in Computer Science*, pages 37–49. Springer, 1999.

[18] E. Ukkonen. On-line construction of suffix trees. *Algorithmica*, 14(3):249–260, 1995.

[19] B. Zhao, K. Iwata, S. Itoh, and T. Kato. A new approach of DCA by using BWT. In *DCC* [10], page 495.

Appendix A

User Manual

Usage: `dca [OPTION]... <FILE>`
Compress on uncompress FILE (by default, compress FILE).

`-d`	decompress
`-f <filename>`	output file
`-l <level>`	maximal antiword length
`-h`	show help
`-v`	be verbose

Options:

`-d`	Decompress specified FILE.
`-f <filename>`	Save output data to the specified file, in case of compression that is antidictionary + compressed data + checksum, when decompressing it is the original uncompressed data. If file is not specified, output is directed to standard output.
`-l <level>`	Compression level, this option can take values from 1 up to 40 or even more, but larger values don't improve compression much, only require excessive system resources. Default: 30
`-h`	Show help.
`-v`	Be verbose, displaying compression ratio, antidictionary and compressed data size and time taken. This is useful for measurements.

Examples:

Compress file "foo" and save it to "foo.dz":

```
dca -f foo.dz foo
```

Decompress file "foo.dz" to "foo":

```
dca -d -f foo foo.dz
```

Compress file "foo" using level 40 and save it to "foo.dz":

```
dca -l40 -f foo.dz foo
```