High Performance BWT-based Encoders *

Dragoş N. Trincă

Faculty of Computer Science, “Al.I.Cuza” University, 700483 Iasi, Romania

Abstract

In 1994, Burrows and Wheeler [5] developed a data compression algorithm which performs significantly better than Lempel-Ziv based algorithms. Since then, a lot of work has been done in order to improve their algorithm, which is based on a reversible transformation of the input string, called BWT (the Burrows-Wheeler transformation). In this paper, we propose a compression scheme based on BWT, MTF (move-to-front coding), and a version of the algorithms presented in [13].

Key words: adaptive codes, the Burrows-Wheeler transformation (BWT), coding theory, data compression, move-to-front coding (MTF)

1 Introduction

A very promising development in the field of lossless data compression is the algorithm by Burrows and Wheeler [5]. Since its publication in 1994, their algorithm has been widely studied, improved, and implemented on different platforms. Their original algorithm, as reported in [5], achieves speed comparable to Lempel-Ziv based algorithms and compression performance close to the best PPM techniques [2].

The most interesting and unusual step in their compression scheme is a reversible transformation of the input string (the Burrows-Wheeler transformation, or BWT), which reorders the symbols such that the newly created string contains the same symbols, but is easier to compress with simple locally adaptive algorithms such as move-to-front coding (MTF) [3].

In this paper, we propose a compression scheme based on BWT, MTF, adaptive codes [13,14], and a version of the algorithms presented in [13]. More

* Research supported in part by CNCSIS grant 632/2004.

Email address: dragost@infoiasi.ro.
specifically, the following sections are aimed to present a detailed description of our algorithm in a progressive manner, including reports of experimental results. As we shall see, experiments performed on various well-known proteins prove that on this type of information our algorithm significantly outperforms the bzip2 utility [11], which is a well-known implementation of the algorithm introduced by Burrows and Wheeler.

2 Adaptive codes

Adaptive codes have been recently presented in [13,14] as a new class of non-standard variable-length codes. The aim of this section is to briefly review some basic definitions and notations. For more details, the reader is referred to [13,14].

We denote by $|S|$ the cardinality of the set $S$; if $x$ is a string of finite length, then $|x|$ denotes the length of $x$. The empty string is denoted by $\lambda$. For an alphabet $\Delta$, we denote by $\Delta^n$ the set $\{s_1s_2\ldots s_n \mid s_i \in \Delta \text{ for all } i\}$, by $\Delta^*$ the set $\bigcup_{n=0}^{\infty} \Delta^n$, and by $\Delta^+$ the set $\bigcup_{n=1}^{\infty} \Delta^n$, where $\Delta^0$ denotes the set $\{\lambda\}$. Also, we denote by $\Delta^{\leq n}$ the set $\bigcup_{i=0}^{n} \Delta^i$, and by $\Delta^{\geq n}$ the set $\bigcup_{i=n}^{\infty} \Delta^i$.

Let $X$ be a finite and nonempty subset of $\Delta^+$, and $w \in \Delta^+$. A decomposition of $w$ over $X$ is any sequence of strings $u_1, u_2, \ldots, u_h$ with $u_i \in X$, $1 \leq i \leq h$, such that $w = u_1u_2\ldots u_h$. A code over $\Delta$ is any nonempty set $C \subseteq \Delta^*$ such that each string $w \in \Delta^+$ has at most one decomposition over $C$. A prefix code over $\Delta$ is any code $C$ over $\Delta$ such that no string in $C$ is proper prefix of another string in $C$. If $u, v$ are two strings, then we denote by $uv$ the catenation of $u$ with $v$.

**Definition 1** Let $\Sigma$ and $\Delta$ be alphabets. A function $c : \Sigma \times \Sigma^{\leq n} \rightarrow \Delta^+$, $n \geq 1$, is called adaptive code of order $n$ if its unique homomorphic extension $\overline{c} : \Sigma^* \rightarrow \Delta^+$ defined by:

- $\overline{c}(\lambda) = \lambda$
- $\overline{c}(\sigma_1\sigma_2\ldots\sigma_m) = c(\sigma_1, \lambda) \cdot c(\sigma_2, \sigma_1) \cdot c(\sigma_3, \sigma_2\sigma_1) \cdot \ldots \cdot c(\sigma_{n-1}, \sigma_{n-2}, \ldots, \sigma_2, \sigma_1) \cdot c(\sigma_n, \sigma_{n-1}, \sigma_{n-2}, \ldots, \sigma_1) \cdot \ldots \cdot c(\sigma_m, \sigma_{m-n} \sigma_{m-n+1} \ldots \sigma_{m-1})$

for all $\sigma_1\sigma_2\ldots\sigma_m \in \Sigma^+$, is injective.

As it is clearly specified in the definition above, an adaptive code of order $n$ associates a variable-length codeword to the symbol being encoded depending on the previous $n$ symbols in the input data string. Let us take an example in order to better understand this mechanism.
Example 2 Let $\Sigma = \{a, b, c\}, \Delta = \{0, 1\}$ be alphabets, and $c : \Sigma \times \Sigma \leq 2 \to \Delta^+$ a function constructed by the following table. One can easily verify that $c$ is injective, and according to Definition 1, $c$ is an adaptive code of order two.

| $\Sigma \setminus \Sigma \leq 2$ | a | b | c | aa | ab | ac | ba | bb | bc | ca | cb | cc | $\lambda$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 01 | 10 | 10 | 00 | 11 | 10 | 01 | 10 | 11 | 11 | 11 | 0 | 0 |
| b | 10 | 00 | 11 | 11 | 01 | 00 | 00 | 11 | 01 | 10 | 00 | 10 | 11 |
| c | 11 | 01 | 01 | 10 | 00 | 11 | 11 | 00 | 00 | 00 | 10 | 11 | 10 |

Let $x = \text{abacca} \in \Sigma^+$ be an input data string. Using the definition above, we encode $x$ by $c(x) = c(a, \lambda)c(b, a)c(a, ab)c(c, ba)c(c, ac)c(a, cc) = 0101111110$.

Let $c : \Sigma \times \Sigma \leq n \to \Delta^+$ be an adaptive code of order $n$, $n \geq 1$. We denote by $C_{c, \sigma_1 \sigma_2 \ldots \sigma_h}$ the set $\{c(\sigma, \sigma_1 \sigma_2 \ldots \sigma_h) \mid \sigma \in \Sigma\}$, for all $\sigma_1 \sigma_2 \ldots \sigma_h \in \Sigma \leq n - \{\lambda\}$, and by $C_{c, \lambda}$ the set $\{c(\sigma, \lambda) \mid \sigma \in \Sigma\}$. We write $C_{c, \sigma_1 \sigma_2 \ldots \sigma_h}$ instead of $C_{c, \sigma_1 \sigma_2 \ldots \sigma_h}$, and $C_{c, \lambda}$ instead of $C_{c, \lambda}$ whenever there is no confusion. Let us denote by $AC(\Sigma, \Delta, n)$ the set $\{c : \Sigma \times \Sigma \leq n \to \Delta^+ \mid c$ is an adaptive code of order $n\}$.

Theorem 3 Let $\Sigma$ and $\Delta$ be two alphabets and $c : \Sigma \times \Sigma \leq n \to \Delta^+$ a function, $n \geq 1$. If $C_u$ is prefix code, for all $u \in \Sigma \leq n$, then $c \in AC(\Sigma, \Delta, n)$.

3 A high performance BWT-based compression scheme

As we have already pointed out, the algorithm introduced in 1994 by Burrows and Wheeler [5] is one of the greatest developments in the field of lossless data compression.

Their algorithm has received special attention not only for its Lempel-Ziv like execution speed and compression performance close to the best statistical modelling techniques [2], but also for the algorithms it combines. Let us briefly describe the three steps in their compression scheme.

BWT. Let $S$ be a string of length $n$ which is to be compressed. The idea is to apply a reversible transformation (called BWT, or the Burrows-Wheeler transformation) to the string $S$ in order to form a new string $S'$, which contains the same symbols. The purpose of this transformation is to group together instances of a symbol $x_i$ occurring in $S$. More precisely, if a symbol $x_i$ is very often followed by $x_j$ in $S$, then the occurrences of $x_i$ tend to be grouped together in $S'$. Thus, $S'$ has a high locality of reference and is easier to compress with simple locally adaptive compression schemes such as move-to-front coding (MTF).
MTF. The idea of move-to-front coding (MTF) is based on self-organizing linear lists. Let $L$ be a linear list containing the symbols which occur in $S'$. If $x_i$ is the current symbol in $S'$ which is to be encoded, then the encoder looks up the current position of $x_i$ in $L$, outputs that position and updates $L$ by moving $x_i$ to the front of the list.

EC. A final entropy coding (EC) step follows the move-to-front encoder. Since the output of MTF usually consists of small integers, it can be efficiently encoded using a Huffman encoder.

This is the algorithm which has led to the development of one of the best techniques in the field of lossless data compression. Let us present a detailed description of BWT and MTF, since our encoder is also based on these algorithms.

**Algorithm BWT.** Let $\Sigma = \{\sigma_0, \sigma_1, \ldots, \sigma_{p-1}\}$ be an ordered set, and let $S = s_1s_2\ldots s_n$ be a string over $\Sigma$, that is, $s_i \in \Sigma$ for all $i \in \{1, 2, \ldots, n\}$. If $M$ is a matrix, $M[i, j]$ denotes the $j$-th element (from left to right) of the $i$-th row.

**INPUT:** the string $S = s_1s_2\ldots s_n$ of length $n$.

1. Let $M$ be a $n \times n$ matrix whose elements are symbols, and whose rows are the rotations (cyclic shifts) of $S$, sorted in lexicographical order. Precisely, if $s_{k_1}s_{k_2}\ldots s_{k_n}$ is the $i$-th rotation of $S$ (in lexicographical order), then $M[i, j] = s_{k_j}$ for all $j \in \{1, 2, \ldots, n\}$.
2. Let $I$ be the index of the first row in $M$ which contains the string $S$ (there is at least one such row). Exactly, $I$ is the smallest integer such that $M[I, j] = s_j$ for all $j \in \{1, 2, \ldots, n\}$.
3. Let $S' = t_1t_2\ldots t_n$ be the string contained in the last column of the matrix $M$, that is, $t_i = M[i, n]$ for all $i \in \{1, 2, \ldots, n\}$.

**OUTPUT:** the 2-tuple $(S', I)$.

Interestingly enough, there exists an efficient algorithm which reconstructs the original string $S$ using only $S'$ and $I$. However, the paper by Burrows and Wheeler [5] gives a very detailed description of this algorithm, so we won’t get into it. Instead, let us explain why the transformed string $S'$ compresses much better than $S$. Consider a symbol $x_i$ which is very often followed by $x_j$ in $S$. Since the rows of $M$ are the sorted rotations of $S$, and the symbol $M[i, n]$ precedes the symbol $M[i, 1]$ in $S$, for all $i \in \{1, 2, \ldots, n\}$, some consecutive rotations that start with $x_j$ are likely to end in $x_i$. This is why $S'$ has a high locality of reference, and is easier to compress with locally adaptive compression schemes such as MTF.

Let us now introduce some useful notation. Let $U = (u_1, u_2, \ldots, u_k)$ be a $k$-tuple. We denote by $U.i$ the $i$-th component of $U$, that is, $U.i = u_i$ for
all $i \in \{1, 2, \ldots, k\}$. The 0-tuple is denoted by $()$. The length of a tuple $U$ is denoted by $\text{Len}(U)$. If $\mathcal{V} = (v_1, v_2, \ldots, v_b)$, $\mathcal{M} = (m_1, m_2, \ldots, m_r, U)$, $\mathcal{N} = (n_1, n_2, \ldots, n_s, \mathcal{V})$, $\mathcal{P} = (p_1, \ldots, p_{i-1}, p_i, p_{i+1}, \ldots, p_t)$ are tuples, and $q$ is an element or a tuple, then we define $\mathcal{P} \triangleright q$, $\mathcal{P} \triangleright i$, $U \triangle \mathcal{V}$, and $M \triangle N$ by:

- $\mathcal{P} \triangleright q = (p_1, \ldots, p_t, q)$
- $\mathcal{P} \triangleright i = (p_1, \ldots, p_{i-1}, p_i, p_{i+1}, \ldots, p_t)$
- $U \triangle \mathcal{V} = (u_1, u_2, \ldots, u_k, v_1, v_2, \ldots, v_b)$
- $M \triangle N = (m_1 + n_1, m_2 + 1, \ldots, m_r + 1, n_2 + 1, \ldots, n_s + 1, U \triangle \mathcal{V})$

where $m_1, m_2, \ldots, m_r, n_1, n_2, \ldots, n_s$ are integers.

**Algorithm MTF.** Let $S' = t_1 t_2 \ldots t_n$ be the string obtained above. The MTF encoder works as follows.

**INPUT:** the string $S' = t_1 t_2 \ldots t_n$ of length $n$.

1. Consider a linear list $L$ which contains the symbols occurring in $S'$ exactly once, sorted in lexicographical order. Also, let $\mathcal{R} = ()$.
2. For each $i = 1, 2, \ldots, n$ execute:
   1. Let $q$ be the number of elements preceding $t_i$ in $L$.
   2. $\mathcal{R} := \mathcal{R} \triangleright q$.
   3. In the list $L$, move $t_i$ to the front of the list.

**OUTPUT:** the $n$-tuple $\mathcal{R}$.

**Example 4** Let $\Sigma = \{a, c, e, h, r, s\}$ be an alphabet, and consider the string $S = \text{research}$ over $\Sigma$. One can verify that:

$$\begin{bmatrix}
a & r & c & h & r & e & s & e \\
c & h & r & e & s & e & a & r \\
e & s & e & a & r & c & h & r \\
e & s & e & a & r & c & h & r \\
h & r & e & s & a & r & c & h \\
r & c & h & r & e & s & a & r \\
r & e & s & a & r & c & h & r \\
s & e & a & r & c & h & r & e
\end{bmatrix}$$

is the matrix containing the sorted rotations of $S$, $I = 7$, $S' = \text{ersrcahe}$, and $\mathcal{R} = (2, 4, 5, 1, 4, 4, 5, 5)$.

At this point, it should be clear that applying BWT and MTF as described
so far, the compression of the string $S$ is reduced to the compression of the tuple $R$. Also, it is trivial to see that if $S$ is sufficiently large (at least several kilobytes), then the tuple $R$ will consist mostly of large blocks of zeroes. For other details on these algorithms (including implementation details) the reader is referred to [5].

New algorithms for data compression, based on adaptive codes of order one, have been recently presented in [13,14], where we have behaviorally shown that for a large class of input strings, our algorithms substantially outperform the well-known Lempel-Ziv compression technique [17,18]. The final encoder in our compression scheme is based on the algorithms proposed in [13]. Before describing it in great detail, let us review the Huffman algorithm, since our encoder is based partly on this well-known compression technique. For further details on the Huffman algorithm, the reader is referred to [7,10].

Algorithm Huffman. As described below, the well-known Huffman algorithm takes as input a tuple $F = (f_1, f_2, \ldots, f_n)$ of frequencies, and returns a tuple $V = (v_1, v_2, \ldots, v_n)$ of codewords, such that $v_i$ is the codeword corresponding to the symbol with the frequency $f_i$, for all $i \in \{1, 2, \ldots, n\}$.

**INPUT:** a tuple $F = (f_1, f_2, \ldots, f_n)$ of frequencies.

1. Consider the $n$-tuples $L = ((f_1, 0, (1)), (f_2, 0, (2)), \ldots, (f_n, 0, (n)))$ and $V = (\lambda, \lambda, \ldots, \lambda)$.
2. If $n = 1$ then $V.1 := 0$.
3. While Len($L$) > 1 execute:
   3.1. Let $i < j$ be the smallest integers such that $L.i.1, L.j.1$ are the smallest elements of the set \{Len($L.q$) | $q \in \{1, 2, \ldots, n\}$\}.
   3.2. $F := \{L.i.Len(L.i).r | r \in \{1, 2, \ldots, Len(L.i.Len(L.i))\}\}$.
   3.3. $S := \{L.j.Len(L.j).r | r \in \{1, 2, \ldots, Len(L.j.Len(L.j))\}\}$.
   3.4. For each $x \in F$ execute $V.x := 0 \cdot V.x$.
   3.5. For each $x \in S$ execute $V.x := 1 \cdot V.x$.
   3.6. $U := L.i \triangle L.j$; $L := L \triangleright j$; $L := L \triangleright i$; $L := L \triangle U$.

**OUTPUT:** the tuple $V$.

Algorithm AE (Adaptive Encoder). The final encoding step in our compression scheme is based on the algorithms presented in [13], that is, on adaptive codes of order one. As we have already discussed, the input of this final encoder is the output of MTF, that is, the tuple $R$. Let $\Sigma = \{\sigma_1, \sigma_2, \ldots, \sigma_p\}$ be an alphabet, and let $x$ be a string over $\Sigma$. Let $q$ be the number of symbols occurring in $x$ (thus, $q \leq p$). Let us explain the main idea of our scheme. Consider that $u \in \Sigma^n$ is some substring of the input string $x$. Also, let us denote by $Follow(u)$ the set of symbols that follow the substring $u$ in $x$. For each symbol $c \in Follow(u)$, let us denote by $Freq(c, u)$ the frequency of the substring $uc$ in
One can easily remark that \(\text{Follow}(u)\) cannot contain more than \(q\) symbols. Moreover, in the most cases, the number of symbols in \(\text{Follow}(u)\) is significantly smaller than \(q\). Instead of applying the Huffman’s algorithm to the \(q\) symbols occurring in \(x\), we apply it to the set \(\{\text{Freq}(c, u) \mid c \in \text{Follow}(u)\}\), since this set has a smaller number of frequencies. If \(\text{code}(c, u)\) is the codeword associated to \(\text{Freq}(c, u)\), then we encode \(c\) by \(\text{code}(c, u)\) if it is preceded by \(u\). Thus, we get smaller codewords.

This procedure is actually applied to every substring \(u\) of length \(n\) occurring in \(x\). Thus, we associate to each symbol a set of codewords, and encode every symbol with one of the codewords in its set, depending on the previous \(n\) symbols. The complete algorithm is given above. Let us now explain what exactly the algorithm performs at each step. The first three steps are aimed to initialize the functions needed. Note that the function \(d\) actually allows us to access the elements of \(\Sigma^n\) in a certain order. In the fourth step, \(b(x_i, x_{i-n} \ldots x_{i-1})\) is switched to 1, since the substring \(x_{i-n} \ldots x_{i-1}x_i\) occurs at least once in \(x\).
and the frequency of \( x_{i-n} \ldots x_{i-1} x_i \) is incremented. In the fifth step, for every substring \( d(j) \) of length \( n \), we apply the Huffman’s algorithm to the symbols following \( d(j) \) in \( x \). In the next two steps, \( \mathcal{Y} \) is a tuple of codewords constructed as follows. If \( c \in \Sigma \) and \( u \in \Sigma^n \), then \( a(c, u) \) is appended to \( \mathcal{Y} \) if and only if \( a(c, u) \neq \lambda \), that is, if \( c \in \text{Follow}(u) \) and \( |\text{Follow}(u)| \geq 2 \). Finally, in the last step, \( Z \) denotes the compression of \( x_{n+1} \ldots x_t \).

So, the compression of the string \( x \) is actually \( Z \). The first three components of the output \( (x_1 x_2 \ldots x_n, b, \mathcal{Y}) \) are only needed when decoding \( Z \) into \( x \).

Let us now take an example in order to better understand the description above.

**Example 5** Let \( \Sigma = \{a, b\} \) be an alphabet, and let us take \( x = \text{baabbabab} \in \Sigma^+ \) as an input data string. After applying EAH2 to \( x \), we get the results reported in the tables below.

Table 1
The function \( a \) after EAH2(\( x \)).

| \( \Sigma \) | \( \Sigma^2 \) | aa | ab | ba | bb |
|-------------|-------------|----|----|----|----|
| a           | \( \lambda \) | 0  | 0  | \( \lambda \) |    |
| b           | \( \lambda \) | 1  | 1  | \( \lambda \) |    |

Table 2
The function \( b \) after EAH2(\( x \)).

| \( \Sigma \) | \( \Sigma^2 \) | aa | ab | ba | bb |
|-------------|-------------|----|----|----|----|
| a           | 0           | 1  | 1  | 1  |    |
| b           | 1           | 1  | 1  | 0  |    |

Table 3
The function \( c \) after EAH2(\( x \)).

| \( \Sigma \) | \( \Sigma^2 \) | aa | ab | ba | bb |
|-------------|-------------|----|----|----|----|
| a           | 0           | 1  | 1  | 1  |    |
| b           | 1           | 1  | 2  | 0  |    |

Let us explain these results by considering the third column of each table. In the second table, \( b(a, \text{ba}) = 1 \) and \( b(b, \text{ba}) = 1 \), since the substrings \( \text{baa} \) and \( \text{bab} \) both occur at least once in \( x \). In the third table, \( c(a, \text{ba}) = 1 \) is the frequency of \( \text{baa} \) in \( x \), and \( c(b, \text{ba}) = 2 \), since \( \text{bab} \) occurs twice in \( x \). Thus, applying the Huffman’s algorithm to the set of frequencies \( \{1, 2\} \), we encode \( a \) (if it is preceded by \( \text{ba} \)) by \( a(a, \text{ba}) = 0 \). Also, if \( b \) is preceded by \( \text{ba} \), then we encode it by \( a(b, \text{ba}) = 1 \).
Considering that the function \( d \) is given by \( d(1) = aa, d(2) = ab, d(3) = ba, \) and \( d(4) = bb \), one can verify that the output of \( \text{EAH2} \) in this example is the 4-tuple:

\[
(ba, b, (0, 0, 1, 1), 01101),
\]

where \( b \) is the function given above. Also, one can remark that the function \( b \) can be encoded using \( p^{n+1} \) bits. In our example, \( b \) can be encoded by \( 2^3 = 8 \) bits, since \( p = 2 \) and \( n = 2 \).

As one can remark, some new notations have already been used above. Specifically, if \( A \) is an algorithm and \( x \) its input, then we denote by \( A(x) \) its output. Also, \( \mathbb{N} \) denotes the set of natural numbers.

**Algorithm Encoder1.** We are now ready to describe our compression scheme based on BWT, MTF, and adaptive codes of order one. Consider the alphabet \( \Sigma = \{\sigma_0, \sigma_1, \ldots, \sigma_{p-1}\} \) fixed above.

**INPUT:** the string \( S = s_1s_2 \ldots s_n \) of length \( n \) over \( \Sigma \).

1. \( X := \text{BWT}(S) \).
2. \( Y := \text{MTF}(X.1) \).
3. \( Z := \text{AE}(Y) \).

**OUTPUT:** the 2-tuple \((X.2, Z)\).

As we have already pointed out in the beginning of this paper, our compression scheme performs much better on proteins than on other type of information. For this reason, we will report experimental results obtained only on this type of files. Specifically, we have tested our compressor on five well-known biological sequences: E.coli, hi, hs, mj, and sc. The last four files form the Protein Corpus [8]. Let us briefly describe each file separately.

**E.coli.** One of the most studied biological sequences, *Escherichia coli* (usually abbreviated to E.coli), is a bacterium that lives in warm-blooded organisms. This genome is the only biological sequence included in the Large Canterbury Corpus [1].

**hi.** *Haemophilus influenzae* (abbreviated H.influenzae, or hi) is a bacterium that causes ear and respiratory infections in children. It was the first fully sequenced genome, made available in 1996. This genome is 1.83 megabases in size, and contains approximately 1740 potential genes. When these genes are translated into proteins, the resulting file is approximately 500 kilobytes in size (representing each amino acid as one byte).

**hs.** *Homo sapiens* (abbreviated H.sapiens, or hs) contains 5733 human genes, and the resulting protein file is approximately 3.3 megabytes in size.

**mj.** *Methanococcus jannaschii* (abbreviated M.jannaschii, or mj) lives in very
hot undersea vents and has a unique metabolism. It is 1.7 megabases in size, contains 1680 genes, and the resulting protein file is approximately 450 kilobytes in size.

**sc. Saccharomyces cerevisiae** (abbreviated S.cerevisiae, or sc) has been studied as a model organism for several decades. At 13 megabases in size, it is one of the largest sequenced organisms.

The results reported below have been obtained by comparing Encoder1 with two of the best compressors available: gzip and bzip2.

**gzip (version 1.3.3).** This is one of the most used UNIX utilities, and is based on Lempel-Ziv coding (LZ77).

**bzip2 (version 1.0.2).** This programme compresses files using the Burrows-Wheeler block sorting text compression algorithm, and Huffman coding. Compression is generally considerably better than that achieved by the LZ77/LZ78-based compressors (including gzip), and approaches the performance of the PPM family of statistical compressors.

| File | Size (bytes) | gzip | bits/ symbol | bzip2 | bits/ symbol | Improvement |
|------|--------------|------|--------------|-------|--------------|-------------|
| E.coli | 4,638,690 | 1,299,066 | 2.24 | 1,251,004 | 2.16 | 48,062 | 3.70 |
| hi | 509,519 | 297,517 | 4.67 | 275,412 | 4.32 | 22,105 | 7.43 |
| hs | 3,295,751 | 1,897,311 | 4.61 | 1,753,321 | 4.26 | 143,990 | 7.59 |
| mj | 448,779 | 257,373 | 4.59 | 239,480 | 4.27 | 17,893 | 6.95 |
| sc | 2,900,352 | 1,682,108 | 4.64 | 1,558,813 | 4.30 | 123,295 | 7.33 |
| **Total** | **11,793,091** | **5,433,375** | – | **5,078,030** | – | **355,345** | – |

| File | Size (bytes) | bzip2 | bits/ symbol | Encoder1 | bits/ symbol | Improvement |
|------|--------------|-------|--------------|----------|--------------|-------------|
| E.coli | 4,638,690 | 1,251,004 | 2.16 | 1,159,813 | 2.00 | 91,191 | 7.29 |
| hi | 509,519 | 275,412 | 4.32 | 274,115 | 4.30 | 1,297 | 0.47 |
| hs | 3,295,751 | 1,753,321 | 4.26 | 1,728,061 | 4.19 | 25,260 | 1.44 |
| mj | 448,779 | 239,480 | 4.27 | 238,294 | 4.25 | 1,186 | 0.50 |
| sc | 2,900,352 | 1,558,813 | 4.30 | 1,539,390 | 4.25 | 19,423 | 1.25 |
| **Total** | **11,793,091** | **5,078,030** | – | **4,939,673** | – | **138,357** | – |

Given the results reported here, one can conclude that our compression scheme is one of the most competitive algorithms in the field of biological data compression.
Further work in this field is intended to compare our compression scheme with some of the best PPM techniques as they are being developed for (biological) data compression. We welcome any suggestions or comments, especially from the readers interested in these matters.

References

[1] R. Arnold, T.C. Bell, The Large Canterbury Corpus. Available electronically at http://corpus.canterbury.ac.nz or http://www.data-compression.info.

[2] T.C. Bell, I.H. Witten, J.G. Cleary, Modeling for text compression, *ACM Computing Surveys* 21(4) (1989) 557–591.

[3] J.L. Bentley, D.D. Sleator, R.E. Tarjan, V.K. Wei, A locally adaptive data compression scheme, *Communications of the ACM* 29(4) (1986) 320–330.

[4] J. Berstel, D. Perrin, *Theory of Codes* (Academic Press, 1985).

[5] M. Burrows, D.J. Wheeler, *A Block-sorting Lossless Data Compression Algorithm*, DEC SRC Research Report 124, 1994.

[6] P. Elias, Universal codeword sets and representations of the integers, *IEEE Transactions on Information Theory* 21(2) (1975) 194–203.

[7] M. Nelson, J. Gailly, *The Data Compression Book* (M&T Books, New York, NY, USA, 1996, 2nd edition).

[8] C.G. Nevill-Manning, I.H. Witten, The Protein Corpus. Available electronically at http://www.data-compression.info.

[9] V.S. Pless, W.C. Huffman (Eds.), *Handbook of Coding Theory* (Elsevier, 1998).

[10] D. Salomon, *Data Compression. The Complete Reference* (Springer-Verlag, 1998).

[11] J. Seward, The bzip2 official home page: http://sources.redhat.com/bzip2.

[12] D. Trincă, Adaptive Codes: A New Class of Non-standard Variable-length Codes (to appear in *Romanian Journal of Information Science and Technology*).

[13] D. Trincă, Towards New Algorithms for Data Compression using Adaptive Codes, In *Proceedings of the 5th International Conference on Information Technology: Coding and Computing* (Las Vegas, Nevada, USA, 2004) 767–771. IEEE Computer Society Press.

[14] D. Trincă, Meta-EAH: An Adaptive Encoder based on Adaptive Codes. Moving between Adaptive Mechanisms, In *Proceedings of the 3rd International Symposium on Information and Communication Technologies* (Las Vegas, Nevada, USA, 2004) 220–225. ACM Library.
[15] F.L. Țiplea, E. Mäkinen, C. Enea, SE-Systems, Timing Mechanisms and Time-Varying Codes, *International Journal of Computer Mathematics* 79(10) (2002) 1083–1091.

[16] F.L. Țiplea, E. Mäkinen, D. Trincă, C. Enea, Characterization Results for Time-Varying Codes, *Fundamenta Informaticae* 53(2) (2002) 185–198.

[17] J. Ziv, A. Lempel, A universal algorithm for sequential data compression, *IEEE Transactions on Information Theory* 23(3) (1977) 337–343.

[18] J. Ziv, A. Lempel, Compression of individual sequences via variable-rate coding, *IEEE Transactions on Information Theory* 24(5) (1978) 530–536.