

# ON DIGITAL SEARCH TREES

## *A Simple Method for Constructing Balanced Binary Trees*

Franjo Plavec, Zvonko G. Vranesic and Stephen D. Brown

*Department of Electrical and Computer Engineering, University of Toronto, 10 King's College Road, Toronto, ON, Canada*

**Keywords:** Data structures, Binary trees, Balanced trees, Digital search trees.

**Abstract:** This paper presents digital search trees, a binary tree data structure that can produce well-balanced trees in the majority of cases. Digital search tree algorithms are reviewed, and a novel algorithm for building sorted trees is introduced. It was found that digital search trees are simple to implement because their code is similar to the code for ordinary binary search trees. Experimental evaluation was performed and the results are presented. It was found that digital search trees, in addition to being conceptually simpler, often outperform other popular balanced trees such as AVL or red-black trees. It was found that good performance of digital search trees is due to better exploitation of cache locality in modern computers.

## 1 INTRODUCTION

Binary trees are a well-known data structure with expected access time  $O(\log_2 n)$ , where  $n$  is the number of nodes (elements) stored in the tree. However, worst-case time is  $O(n)$  if the elements are added to the tree in a specific order, which makes the tree unbalanced. To avoid this, many techniques for balancing binary trees have been proposed. Since most operations on binary trees run in the worst case in  $O(h)$  time, where  $h$  is the height of the tree, keeping the tree balanced is the key to good performance.

Most balancing techniques do not keep the tree perfectly balanced, but only impose a limit on the maximal height of the tree (Cormen, 1998). We will use this relaxed definition of balanced trees throughout this paper. Two well-known balanced trees are the red-black trees and the AVL trees (Cormen, 1998). These trees maintain additional information in each node (color or node height) and manipulate the tree to keep it balanced as nodes are added to or removed from the tree.

Both of these techniques are fairly complex; they require keeping additional information in the nodes, such as the node color, and performing fairly complex "rotation" operations when the nodes are inserted or deleted. The same is true for most other tree balancing techniques, which makes them unpopular in practice. According to (Andersson, 1993), even algorithms taught in introductory university courses are

not used in practice if they are too complex. This provides a motive for finding simple data structures and algorithms that are easy to understand and code. In this light, we believe that digital search trees (DSTs), a data structure first described in (E. Coffman, 1970), represents such a simple data structure for balancing binary trees.

In an ordinary binary tree a decision on how to proceed down the tree is made based on a comparison between the key in the current node and the key being sought. DSTs use the values of bits in the key being sought to guide this decision. This approach has many desirable properties. First, the algorithms for node placement and search are conceptually simple and intuitive; implementing insert and search methods for DSTs requires only a few modifications to the corresponding routines for ordinary binary trees. The delete routine for DSTs is conceptually simpler than that for ordinary binary trees. Second, this approach does not require keeping additional information in the nodes to maintain the tree balanced, which removes the space overhead of the other two approaches. The tree is balanced because the depth of the tree is limited by the length (number of bits) of the key.

DSTs have not been popular for several reasons. According to Flajolet and Sedgewick, "digital search trees are easily confused with *radix search tries*, a different application of essentially the same idea" (F. Flajolet, 1986). As a consequence, most programmers are not even aware of their existence,

and tend to associate advantages and drawbacks of tries with those of DSTs. For instance, at the time of writing of this paper, Wikipedia does not even list the DSTs as one of the tree data structures, while many other structures, including AVL trees, AA trees, splay trees, tries, etc. are listed (Wikipedia, The Free Encyclopedia, 2007).

The second reason for low popularity of DSTs is that they are sensitive to bit distribution. Namely, these trees will be skewed if the probability of occurrence of 0 and 1 digits is not equal (Knuth, 1997). In this paper we show that although this is true, the worst case performance is still satisfactory, primarily because of the effects the cache hierarchy has on the performance of modern computers.

The third reason is associated with limited use of DSTs. At first, it was thought that these trees can only be used when all the keys in the tree have equal length, or with variable length keys when no key is a prefix of another. Later, a simple method for storing arbitrary keys of variable lengths into DSTs was devised (Nebel, 1996). Another limitation is due to the fact that DSTs require access to individual bits of the key, which is not easily achievable in some high-level languages. This is a valid concern, but it should not be a reason to prevent the use of these trees by the programmers in languages, such as C, where bit-level data manipulation is not an uncommon task.

Believing that their advantages may outweigh their disadvantages, in this paper we experimentally evaluate the performance of DSTs and compare their performance with alternate approaches. The rest of the paper is organized as follows. The next section gives a description of DSTs and associated algorithms. Experimental evaluation is presented in section 3, and conclusion in section 4.

## 2 DST ALGORITHMS

A digital search tree (DST) is a binary tree whose ordering of nodes is based on the values of bits in the binary representation of a node's key (Knuth, 1997). The ordering principle is very simple: at each level of the tree a different bit of the key is checked; if the bit is 0, the search continues down the left subtree, if it is 1, the search continues down the right subtree. The search terminates when the corresponding link in the tree is NIL. Every node in a DST holds a key and links to the left and right child, just like in an ordinary binary search tree. In contrast, a *trie* does *not* store keys in internal nodes, only in leaves.

Let us define some terms that are used in this paper. A node  $x$  has the *height*  $h_x$ , which is equal to

the number of edges on the longest downward path from the node to a leaf. The *height of the tree*,  $h$ , is equal to the height of its root. A node  $x$  has the *depth*  $d_x$ , which is equal to the number of edges on the path from the node to the root. The *depth of the tree*,  $d$ , is equal to the depth of the leaf with the greatest depth, and is equal to the tree height,  $h$ .

In the following sections we only give intuitive descriptions of algorithms for DSTs. Exact algorithms can be found in (Knuth, 1997) and (Sedgewick, 1990).

### 2.1 Creating and Searching Dsts

Let us build a tree with the following elements: 1001, 0110, 0000, 1111, 0100, 0101, 1110. Since we start with an empty tree, the first element, 1001, becomes the root of the tree. The next key to be inserted is 0110. First, we have to check whether this key is equal to the key of the root node. Since it is not, we continue traversal down the tree. To decide where to place the node, we look at the first bit from the left. Since this bit is 0, we take the path down the left subtree and find that the left pointer is NIL. Therefore, we create a new node, which is the left child of the root node, as shown in Figure 1a. The next element to be inserted is 0000. Since the root of the tree is not NIL (and its key is not equal to the key being inserted), we look at the first bit (from the left) of the key to be inserted. Since this bit is 0, we take the path down the left subtree. Since the next node is not NIL either, we look at the next (second) bit of the key to be inserted. The bit is 0, so we take the path down the left subtree. At this point we encounter a NIL pointer and place the new node in its place, as depicted in Figure 1b. We continue the procedure until all nodes have been added, and the tree in Figure 1f is obtained. Bits used to make the decisions while progressing down the tree are shown in bold in the figure. It is worth noting that scanning the bits from left to right, when making search decisions, is an arbitrary choice. The tree can be built in the same manner by scanning the bits from right to left.

The insertion method for DSTs is nearly identical to the insertion method for binary search trees. We first compare the key to be inserted with the key in the current node, except that for DSTs we test only for equality. In addition, DST algorithms test the corresponding bit of the new key to choose the next move.

To search for an element, we traverse the tree in the same way the insert procedure does. If along the way we find that the current node's key matches the key we are looking for, the search completes successfully. If during the traversal we reach a NIL node, this

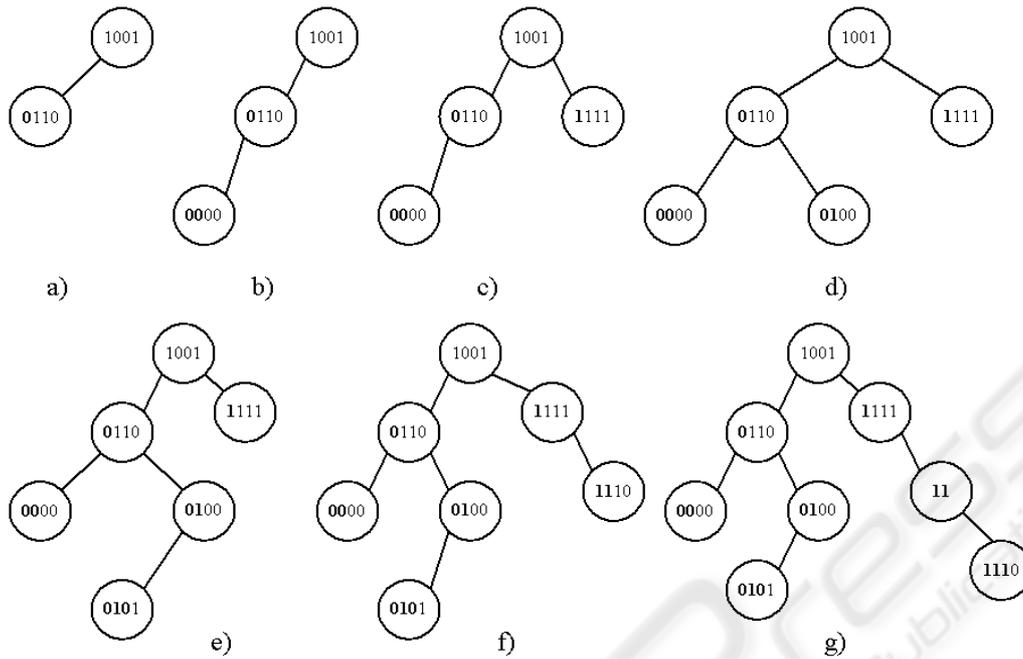


Figure 1: Creating a digital search tree.

means that the search key does not exist in the tree.

The above discussion deals with the case where all keys are of equal length, which happens in many applications (e.g. when the keys are integers). The algorithm requires only a minor modification to handle variable length keys. Consider, for example, how the key 11 can be added to the tree in Figure 1f. As before, we follow the *right* link twice, because the first two bits are 1. At this point we have run out of bits to analyze. In such a case, it is obvious that the node we are currently at has to have a key with a prefix equal to the new key, and has to be longer than the new key (otherwise the two keys are the same). Therefore, we can place the new key (11) in place of the existing node (1110), and continue by inserting the existing node (1110) further down the tree. Since the third bit of 1110 is 1, we go to the right, and place the new node there because we have reached a NIL link. The resulting tree is shown in Figure 1g.

Searching trees with keys of variable length is also simple. If we run out of bits to analyze, the search is terminated because the key sought does not exist in the tree. The algorithms for dealing with keys of variable length were originally presented in (Nebel, 1996).

## 2.2 Deleting Nodes From Dsts

Procedure to delete a node in the DST simply replaces the node with any leaf node in either of the node's subtrees (E. Coffman, 1970). If the node to be deleted

does not have any children, it is simply removed and replaced by a NIL pointer. For instance, removing the node 0110 from the tree in Figure 1g can be done by replacing it with either node 0000 or 0101. It is obvious that this method is similar, and in fact simpler than the deletion method for ordinary binary trees, which has to consider three distinct cases (Cormen, 1998)

## 2.3 Sorted Dsts

A DST is not a *binary search tree*, i.e. printing a DST in-order will not produce a sorted sequence of tree's elements. This is not a major concern, because there are many applications that do not require trees to be sorted. However, algorithms for DSTs can be modified to produce a *sorted digital search tree*, providing that all the keys are of the same length, and that the key's binary representation directly defines the ordering. This is the case for unsigned numbers, but not for signed numbers. The most significant bit of a signed number denotes the sign, and does not contribute to the value according to its weight. Therefore, signed numbers cannot be directly organized into a sorted DST. Instead, two sorted DSTs could be created, one for positive and one for negative numbers. Care must be taken to order negative numbers appropriately.

Sorted DSTs can also be implemented when the keys are strings of variable length, by padding all the keys to the same length, either by explicitly padding any unused characters with a terminating character ('\0' in C), or by constructing the algorithm to be-

have as if the terminating characters were there. To the best of our knowledge, no other publication has discussed a technique to sort DSTs.

The following algorithm for constructing sorted DSTs uses an idea similar to the one used in (Nebel, 1996). For the algorithm to work, the bits have to be scanned from the most-significant to the least significant as the tree is traversed. The procedure takes two arguments,  $T$  and  $x$ , where  $T$  is a (possibly empty) sorted DST, and  $x$  is a node to be inserted into the tree, containing a key  $k_x$ , and pointers left and right set to NIL. It is assumed that the key  $k_x$  can be represented as a sequence of bits  $k_x[n-1], k_x[n-2], \dots, k_x[0]$ .

**Algorithm 2.1:** INSERT( $T, x$ )

```

y ← root(T)
z ← NIL
i ← n
while y ≠ NIL
  i ← i - 1
  c ← kx - ky
  if c = 0
    then return
  if (c > 0 and kx[i] = 0) or (c < 0 and kx[i] = 1)
  do
    { temp ← ky
      ky ← kx
      kx ← temp
    }
    z ← y
    if kx[i] = 0
      then y ← left(y)
    else y ← right(y)
if z = NIL
  then root(T) ← x
  else if kx[i] = 0
    then left(z) ← x
  else right(z) ← x

```

At each step down the tree, we analyze the corresponding bit of  $k_x$  to choose the appropriate path down the tree and compare the new key  $k_x$  with the current key  $k_y$ . If the corresponding bit is 0, and  $k_x < k_y$ , we continue down the left branch, because this preserves both the digital search tree structure and the binary search tree structure. Conversely, if the corresponding bit is 1 and  $k_x > k_y$ , we continue down the right branch. However, if the corresponding bit is 0, and  $k_x > k_y$ , it is impossible to satisfy both properties by proceeding with the node  $x$ . Instead, we insert the node  $x$  in place of the node  $y$ , and continue the insertion down the left branch, now inserting the node  $y$ . The node  $y$  has to go into the left branch, because  $k_y$  is lower than  $k_x$ . Also, its corresponding bit has to be 0, because the bits are ordered from the most significant to the least significant, and since  $k_x$  has the bit equal to 0, and  $k_y < k_x$ ,  $k_y$ 's bit in the same position has to be 0. This ensures that both the digital search tree and the binary search tree structure is preserved. The procedure is similar when the corresponding bit of  $k_x$  is

1, and  $k_x < k_y$ ; we insert  $x$  in place of  $y$ , and proceed down the right branch to insert  $y$  into an appropriate spot. This process eventually terminates when a NIL link is reached.

Sorted DSTs can be searched using the search procedure for either binary search trees or digital search trees, because the sorted DSTs are binary search trees. On the other hand, the delete procedure has to be constructed as follows. If a node  $x$  is to be deleted from the tree, we locate the lowest element in the right subtree ( $x$ 's successor), or the highest element in the left subtree ( $x$ 's predecessor) if there is no right subtree. Let us call that node  $d$ . We now move  $d$  in place of  $x$ , and continue the process by deleting  $d$  from its old place using the same procedure. The process terminates once the selected node  $d$  does not have any children, at which point its deletion is a trivial matter. We can move  $d$  in place of  $x$  because  $d$  is either  $x$ 's predecessor or successor, so the binary search tree structure will be preserved. The digital search tree structure is preserved because a node can be replaced by any of its descendants, because they lie in the same subtree, so the appropriate bits have to match (Knuth, 1997).

## 2.4 Properties of Digital Search Trees

The idea of DSTs can be extended to consider more than one bit at a time. For instance, in an M-ary tree ( $M \geq 2$ ), each node can have more than two children (Knuth, 1997).

A DST with node keys of length  $|k|$  ( $|k| > 0$ ) has the height  $h$  at most equal to  $|k|$  (Sedgewick, 1990). Since all the algorithms described in the previous sections run in  $O(h)$  time, and the height of the tree is limited by the binary length of the key  $|k|$ , all the algorithms run in  $O(|k|)$  time in the worst case. On average, if the keys are distributed uniformly across all possible binary values, these algorithms require  $O(\log_2 n)$ , according to (Sedgewick, 1990). For most other tree data structures the worst-case performance is expressed in terms of the number of elements in the tree. For DSTs the worst case performance is given in terms of the key length, so these expressions are not directly comparable. Therefore, we believe that experimental evaluation is the best way to compare DSTs with other tree structures. We present our experimental evaluation in the following section.

## 3 EXPERIMENTAL EVALUATION

In this section we compare the effectiveness of digital search trees, binary search trees, AVL trees and red-black trees. To make the comparison fair, we used an

existing implementation of binary search trees, AVL and red-black trees. We chose the *GNU libavl* (Pfaff, 2006) library of binary tree routines implemented in C, because of its completeness and extensive documentation. The code for binary search trees, AVL and red-black trees was used as provided in the library. We used the code versions without parent pointers because they were not needed in any of our experiments.

DST code was based on the *libavl* code for binary search trees. Only the necessary changes were made, and all function prototypes were kept the same. Insert and search procedures for DSTs are very similar to those for binary search trees; the only difference is how the choice of the next direction down the tree is made. As a consequence, only a few lines of code for these methods differ between the binary search tree and digital search tree implementation. For instance, for trees that store integer key values, the source code for the *insert* routine differs in only three lines of code, while the *search* routine differs in five lines of code.

In *libavl*, a node contains left and right pointers, and a data pointer, which points to user data, including the key. For the red-black and AVL trees, each node also contains additional data (one character) to implement balancing. We used this default node structure in all our implementations, with the data pointer pointing to the key. No other data was stored in our experiments.

### 3.1 Experimental Setup

All program code is written in C, and compiled with Microsoft's 32-bit C/C++ Optimizing Compiler Version 14.00.50727.42, which ships with the Microsoft Visual C++ 2005 Express Edition. All programs were compiled using the default settings for a *Release* version (/O2 optimization level).

The experiments described in this section were run on a dedicated personal computer with Intel Pentium 4 processor, with 8 Kbytes L1 cache and 512 Kbytes on-chip L2 cache, running at 2GHz, with 1GB memory, and running Windows XP Professional Version 2002, SP2. Each experiment was repeated five times, and the average execution times are reported.

Two groups of experiments were performed. In the first group of experiments integers were used as keys in the binary tree, while character strings were used in the second group. A summary of settings in these experiments is given in Table 1. The columns in the table indicate the data type used in different experiments, and the order in which the elements were inserted into the tree (random, ascending or descending). The ordering refers to the ordering of the keys.

Table 1: List of experiments performed.

Experiment	Data type		Ordering		
	Int	String	Rand.	Asc.	Desc.
I1	X		X		
I2	X			X	
I3	X				X
S1		X	X		
S2		X		X	
S3		X			X
S4		X		X	

Ordered insertion tests the performance of tree structures for the case that is normally the worst-case scenario for the binary search trees.

In all experiments other than S4, the keys were generated randomly, with uniform distribution, and were all of equal length. For experiments I1-I3, the number of elements in the tree was varied from 100,000 to 10,000,000, increasing the number of elements 10 times in each experiment. For experiments S1-S3, the number of elements was varied from 10,000 to 1,000,000 in the same manner. For these experiments we also used three different string lengths: 12, 20 and 40 characters. However, since we did not observe a significant variation in performance trends for different string lengths, we present only the performance results for strings of length 20.

In I1-I3 and S1-S3, two input files with mutually disjoint key sets were used in each experiment. The keys in the first file are used to create a binary tree, and the time required to create the tree is measured. All the keys were brought into a memory array before being added to the tree or any searches being performed. Therefore, the reported execution times do not include any disk accesses initiated by our programs.

Next, a search is performed for every key in the first file, which verifies that all keys have been added and can be located in the tree; search time is measured and recorded. Then, a search for the keys in the first file and the keys in the second file is performed. Since the keys in these files are mutually disjoint, this measures the performance of searches when half the keys sought do not exist in the tree. Next, a search for the keys in the second file is performed, which provides the execution time of searches for keys that do not exist. The keys in the second file were not sorted in any of the experiments, which means that a search for the elements was performed in random order.

Finally, the nodes in the tree are deleted, one by one, in the same order they were inserted in. The time for this operation is measured as well. To make sure that the delete operation does not leave the tree unbalanced, another experiment was performed, where

a search for the keys from the first file is executed at several checkpoints during the deletion process, and the total search time is measured.

Experiment S4 stores a dictionary of strings of variable length, with the maximal length of 24 characters. The dictionary was *The Gutenberg Webster's Unabridged Dictionary* (Project Gutenberg, 2007) with 109,327 words, 93,468 of which were unique. Only the words, not their explanations, were added to the tree. The second file was a novel (English translation of *Les Misérables*, by Victor Hugo) downloaded from the same website, with 567,616 phrases, 489,431 of which were found in the dictionary. Experiment S4 represents a near-worst-case for DSTs, because the keys are of variable length, and many of the keys are prefixes of other keys.

### 3.2 Search Tree Implementations

We implemented several different versions of the program code. For DSTs storing integer keys, we used three different versions: scanning bits from left to right (most-significant to least-significant) while progressing down the tree (*DSTL*), scanning bits from right to left (*DSTR*), and a sorted digital search tree (*DSTS*). Performance of these variants is compared to that of binary search trees (*BST*), AVL trees (*AVL*), and red-black trees (*RB*).

For algorithms for storing strings we used *libavl* implementation of binary search trees, AVL and red-black trees. We only had to modify the comparison function, which originally compared integers. We used the standard C library *strcmp* function for this purpose. We refer to these implementations as *SBST*, *SAVL* and *SRB* to distinguish them from the corresponding implementations using integer keys.

We also tested three different implementations of DSTs storing character string keys. First, we used a straightforward implementation, where individual characters in a string are scanned in order, from left to right, and analyzed bit-by-bit, also from left to right as we progress down the tree. Keys of variable lengths are handled using the algorithm described in (Nebel, 1996). We call this implementation *SDSTC*.

Next, we tried to optimize the performance by observing that most computers perform logical operations (such as bit extraction) on integers, not characters. Therefore, we can look at the string of characters as an array of bits, which can be cast into an arbitrary data. We cast characters into integers, moving along the character array from left to right, four characters at a time. However, we scan the individual integers (after the cast) from right to left. This is because the computer we ran the experiments on has the little-

endian memory organization, so this order of analyzing bits corresponds well (though not completely) to the ordinary left to right scanning order of *SDSTC*. In this implementation we also cast characters into integers in the comparison function, which speeds up the comparison, compared to the implementation using the *strcmp* function. The number of characters in the string has to be divisible by 4 for this to be possible, which is not a severe limitation. We call this implementation *SDSTL*.

Finally, we implemented a sorted version of digital search trees for strings. This implementation is called *SDSTS*; it scans the input string character-by-character from left to right to preserve ordering.

We observed that the keys being analyzed by the algorithms share a common prefix with the key being sought, inserted or deleted from the tree. This common prefix becomes longer as we progress down the tree. Therefore, we can skip these bits when the algorithms check for string equality. If this is done at the character granularity (i.e. only skip 8, 16, 24,... bits once that many tree levels have been traversed), it is easy to implement and reduces the comparison time. We call this technique *reduced comparison*. This technique was employed for *SDSTC* and *SDSTS* implementations, but not for *SDSTL*, because it is more complicated to implement in that implementation, and does not benefit performance.

For *SDSTL* and *SDSTS* implementations, we pad any unused characters with the terminating character `'\0'`. The padding is done at insertion time, as well as when searching for or deleting a node. To make the comparisons fair, we include the time to pad the unused characters in our measurements.

### 3.3 Results

#### 3.3.1 Average Node Depth and Tree Depth

Aside from execution time, we use two metrics to evaluate different algorithms: average node depth and tree depth. The average node depth is relevant because it determines the expected number of steps the algorithms have to perform. The tree depth is defined by the depth of the leaf with the greatest depth. Therefore, it defines the worst case for operations on binary trees.

The average node depths and tree depths for various experiments relative to the performance of AVL/SAVL tree are shown in tables 2 and 3. The results are averages over all tree sizes, because in most cases the relative results do not differ much as the tree size grows. For several experiments we do not give values for *BST*/*SBST*, because not all experiments

Table 2: Average node depth relative to AVL and SAVL.

	RB	BST	DSTL	DSTR	DSTS
I1	1.00	1.34	1.01	1.00	1.01
I2	1.02	N/A	1.04	1.01	1.04
I3	1.02	N/A	1.04	1.01	1.04
	SRB	SBST	SDSTL	SDSTC	SDSTS
S1	1.00	1.35	1.14	1.23	1.24
S2	1.03	N/A	1.16	1.27	1.26
S3	1.03	N/A	1.16	1.26	1.26
S4	1.00	889	2.17	2.38	2.39

Table 3: Tree depth relative to AVL and SAVL.

	RB	BST	DSTL	DSTR	DSTS
I1	1.00	2.09	1.04	1.04	1.07
I2	1.88	N/A	1.31	1.24	1.30
I3	1.88	N/A	1.32	1.23	1.30
	SRB	SBST	SDSTL	SDSTC	SDSTS
S1	1.00	1.97	1.20	1.29	1.29
S2	1.85	N/A	1.41	1.59	1.52
S3	1.85	N/A	1.44	1.57	1.52
S4	1.71	1443	4.35	4.47	4.76

with BSTs were completed because of excessive run-time.

In experiments I2, I3, S2 and S3, the tree depth of red-black trees is significantly higher than that of AVL trees, which is expected, because the red-black trees do not achieve as good balancing as the AVL trees (Cormen, 1998). These results show that the DSTs, including the sorted DSTs, do a good job of keeping the tree balanced, with average node depth comparable to that of AVL and red-black trees, and tree depth between that of AVL and red-black trees, for all but the last experiment (S4). Our experiments showed that these large differences for S4 do not translate into large performance differences.

### 3.3.2 Performance of the Insert Procedure

Table 4 presents the performance of the insert procedure for the largest dataset in each experiment.

DSTL and SDSTL provide the best performance in all cases except for S4. This was the case for all tree sizes, although the ratio becomes smaller as the tree size shrinks. (S)AVL and (S)RB exhibit poorer performance because of complicated rotations they have to perform to keep the tree balanced.

RB and DSTR give much lower relative performance for experiments I2 and I3, which is surprising considering that the tree depth and the average node depth do not vary drastically for these experiments (see tables 2 and 3). The reason is the effect processor caches have on performance; the other algorithms experience improved performance due to cache locality when the inputs are sorted, while RB and DSTR do not. For example, for DSTL, where the bits are

Table 4: Insertion performance relative to AVL and SAVL for largest datasets.

	RB	BST	DSTL	DSTR	DSTS
I1	1.01	1.08	0.82	0.76	1.05
I2	3.00	N/A	0.89	4.19	0.94
I3	2.41	N/A	0.86	3.44	1.03
	SRB	SBST	SDSTL	SDSTC	SDSTS
S1	1.04	1.11	0.65	0.82	1.00
S2	1.66	N/A	0.75	0.91	1.14
S3	1.65	N/A	0.76	0.91	1.11
S4	1.53	587	1.11	1.40	1.75

scanned from left to right, elements are repeatedly inserted into the same branch of the tree. This means that the whole chain of pointers leading to the place for a new node are already in the cache in many cases. Since DSTR analyzes the bits from the right, where the bits vary more often, it is likely to insert a new element into a different branch of the tree most of the time, so it has poor cache locality. Therefore, DSTR is a poor choice for a scanning method and should not be used.

The most interesting result is the one for experiment S4. Although the three digital search trees have an average node depth more than twice the depth of the AVL trees, the SDSTL is only 11% slower than SAVL, and faster than SRB. Even the straightforward implementation, SDSTC, or the sorted version, SDSTS, do not suffer performance penalties proportional to the difference in node depth. This can be explained through better utilization of cache locality. Digital search trees exhibit better cache locality than the red-black and AVL trees for two reasons. First, the nodes in digital search trees are never (or only sometimes for SDSTS) moved from their initial position, thereby better preserving spatial locality. Also, the nodes in digital search trees are smaller because they do not include balancing information, so more can fit into a cache. Consequently, a node and its children are more likely to reside in the same cache line, thus improving the performance. For these reasons, the digital search trees are well suited for execution on modern computers. Although other methods for exploiting cache locality in binary trees exist (Oksanen, 1995), they explicitly manage memory allocation and/or tree structure, which makes the algorithms even more complex. In contrast, digital search trees exhibit good locality implicitly, based on their structure.

We have not shown the results for all tree sizes, but the general trend is that the performance gap between different algorithms, as presented in Table 4, tends to grow linearly as the number of elements in the tree grows exponentially.

### 3.3.3 Search Performance

We do not present all the results for search routines because they are similar to the results for the insert routine. This is not surprising, because these two routines are similar in structure.

We observed a general trend that digital search trees tend to perform better when fewer elements sought are actually found in the tree. One interesting case where this is particularly evident is experiment S4. Table 5 gives the performance results relative to SAVL, as the number of elements that were actually found decreases. The FA and FS rows denote Found All and Found Some, respectively, and correspond to searching for all the words in the dictionary, and searching for the words from the book, as described in section 3.1.

Table 5: Performance for two different searches in experiment S4.

	SRB	SBST	SDSTL	SDSTC	SDSTS
FA	1.01	960	1.39	1.95	2.24
FS	1.05	308	0.90	1.07	1.37

The FA search, in which all the elements sought are found, is the worst case we found for the digital search trees. Even then, only the sorted (SDSTS) and the straightforward implementation (SDSTC) suffer penalties proportional to the average node depth. A more clever implementation, SDSTL, which is still much simpler to implement than the other balanced tree algorithms, suffers a modest penalty of 39% in the worst case. When the elements sought are found less often, the relative performance of *all* DST trees improves significantly.

### 3.3.4 Delete Performance

We do not present the results for delete routines for experiments I1-I3 and S1-S3, because they show similar trends as the insert routine. For the experiment S4, we found that SRB, SDSTL, SDSTC and SDSTS have 15%, 46%, 69%, and 34% worse performance than SAVL, respectively. At the same time, SBST performs 12% better than SAVL when deleting the nodes.

We also checked the search performance at several checkpoints throughout the deletion process, and found that SRB, SDSTL, SDSTC and SDSTS achieve 6%, 20%, 59%, and 79% worse search performance than SAVL, respectively. SBST takes 180 times longer than SAVL in this case. These results resemble the search performance in Table 5.

## 4 CONCLUSIONS

We discussed the digital search trees (DSTs), which use the values of bits in the key to determine the key's position in the tree. We believe that these trees are easier to understand conceptually, and easier to implement in practice than other known balanced trees. We found that only small modifications to algorithms for ordinary binary search trees are needed to implement the digital search trees.

Our experiments show that performance of digital search trees is often as good or better than AVL or red-black trees. The digital search trees can be recommended for use whenever the keys stored are integers, or character strings of fixed width. We found that these trees are also suitable in many cases when the keys are strings of variable length.

We believe that these trees deserve renewed attention. Novel techniques may be discovered that improve the performance even further. Also, new applications may be discovered that could benefit from using the digital search tree as a data structure.

## REFERENCES

- Andersson, A. (1993). Balanced search trees made simple. In *WADS, 3rd Workshop on Algorithms and Data Structures*, pages 60–71. Springer Verlag.
- Cormen, T. H. (1998). *Introduction to Algorithms*. MIT Press, Cambridge, Mass, 2nd edition.
- E. Coffman, J. E. (1970). File structures using hashing functions. *Communications of the ACM*, 13(7).
- F. Flajolet, R. S. (1986). Digital search trees revisited. *SIAM Journal on Computing*, 15(3).
- Knuth, D. E. (1997). *The Art of Computer Programming*, volume 3. Addison-Wesley, Reading, Mass., 2nd edition.
- Nebel, M. E. (1996). Digital search trees with keys of variable length. *Informatique Theorique et Applications*, 30(6):507–520.
- Oksanen, K. (1995). Memory Reference Locality in Binary Search Trees. Master's thesis, Helsinki University of Technology.
- Pfaff, B. (2006). Gnu libavl. <http://adinfo.org>.
- Project Gutenberg (2007). The Gutenberg Webster's unabridged dictionary. <http://www.gutenberg.org/etext/673>.
- Sedgewick, R. (1990). *Algorithms in C*. Addison-Wesley, Reading, Mass.; Toronto.
- Wikipedia, The Free Encyclopedia (2007). Category:trees(structure). <http://en.wikipedia.org/wiki/Category:Trees.%28structure%29>.