

# Analysis of Shift-Or (Bitap) Algorithm for DNA Sequences

## 1. Introduction: Bit-Parallel Matching

The **Shift-Or algorithm** (also known as **Bitap** or **Baeza-Yates-Gonnet algorithm**) is a bit-parallel string matching technique that leverages bitwise operations to achieve high-speed pattern matching. It is especially well-suited for finding a pattern  $P$  (length  $m$ ) in a text  $T$  (length  $n$ ).

Its key innovation is encoding the pattern as a set of **bitmasks** and maintaining a **state vector** (a single integer) that tracks all potential matches simultaneously. This allows it to process the text in  $O(n)$  time, provided the pattern is short enough to fit within a machine word (e.g.,  $m \leq 64$ ).

This document analyzes the algorithm and its adaptation for approximate (fuzzy) matching, which is highly relevant for DNA sequences where small mutations or errors are common.

## 2. The Algorithm: Exact Matching

The algorithm operates in two phases: preprocessing the pattern and searching the text.

### 2.1 Phase 1: Preprocessing (Building Bitmasks)

We create a **mask table**  $B$  for the pattern  $P$ . For each character  $c$  in the alphabet (e.g., {A, C, G, T}),  $B[c]$  is an  $m$ -bit integer.

**Definition:** Bit  $i$  of the mask  $B[c]$  is set to **1** if the character  $P[i] = c$ . Otherwise, the bit is 0.

*Note: For the Shift-Or algorithm, it is common to use 0 for a match and 1 for a mismatch to work with bitwise OR. This analysis will follow the pseudo-code's  $(1 \ll i)$  logic, where a 1 bit represents the position of a character.*

**Example:** For pattern  $P = \text{"ACG"}$  ( $m = 3$ ). We use 0-based indexing from right-to-left.

- $P[0] = \text{'A'} \rightarrow \text{Bit 0}$
- $P[1] = \text{'C'} \rightarrow \text{Bit 1}$
- $P[2] = \text{'G'} \rightarrow \text{Bit 2}$

The corresponding bitmasks are:

- $B[\text{'A'}] = 001$  (binary)
- $B[\text{'C'}] = 010$  (binary)
- $B[\text{'G'}] = 100$  (binary)
- $B[\text{'T'}] = 000$  (binary)

### 2.2 Phase 2: Searching (State Vector Updates)

We maintain a single  $m$ -bit **state vector**  $D$ .

**Interpretation:** Bit  $i$  in  $D$  is **1** if the first  $i+1$  characters of the pattern ( $P[0...i]$ ) match the last  $i+1$  characters of the text scanned so far.

**Initial State:**  $D = 0$  (no matches)

**Update Rule:** For each character  $T[j]$  in the text, we update  $D$ :

$D = ((D \ll 1) \mid 1) \& B[T[j]]$

This single line performs three actions:

- $D \ll 1$ : Shifts all partial matches left by one. A match of  $P[0...i-1]$  now becomes a potential match for  $P[0...i]$ .
- $\mid 1$ : Sets the 0-th bit to 1. This speculates that the current text character  $T[j]$  might be the start of a new match (i.e., it matches  $P[0]$ ).
- $\& B[T[j]]$ : This is the "filter." It keeps a bit in  $D$  set to 1 *only if* the corresponding pattern character  $P[i]$  matches the current text character  $T[j]$ .

**Match Detection:** A complete match is found at position  $j$  if the  $m-1$  bit (the final bit) of  $D$  is 1.

## 3. Algorithm Adaptation: Approximate Matching

To allow up to  $k$  errors (insertions, deletions, or substitutions), we adapt the algorithm by maintaining  $k+1$  state vectors:  $D_0, D_1, D_2, \dots, D_k$

Where  $D_i$  is an  $m$ -bit vector that tracks all matches of the pattern  $P$  that end at the current text position with **exactly  $i$  errors**.

**Update Rule:** When processing text character  $T[j]$ , the new states are calculated based on the *previous* states (before processing  $T[j]$ ), which we'll call  $\text{prev\_D}$ .

- For  $D_0$  (0 errors):** Same as the exact algorithm.  $D_0 = ((\text{prev\_D}_0 \ll 1) \mid 1) \& B[T[j]]$
- For  $D_i$  (1 to  $k$  errors):** The new state  $D_i$  is a bitwise OR of all possibilities that could lead to an  $i$ -error match:
  - Substitution (or Match):** A previous  $i$ -error match extended by one character.  $\text{sub} = ((\text{prev\_D}_{i-1} \ll 1) \mid 1) \& B[T[j]]$
  - Insertion:** A previous  $(i-1)$ -error match, plus one insertion (we skip a pattern character).  $\text{ins} = \text{prev\_D}_{i-1}$

3. **Deletion:** A previous ( $i-1$ )-error match, plus one deletion (we skip a text character).  $del = (prev\_D_{i-1} \ll 1) \mid 1$

The full recurrence relation combines these:  $D_i = sub \mid ins \mid del \mid ((prev\_D_{i-1} \ll 1) \& B[T[j]])$  (The last term handles a match on top of an  $i-1$  error state).

**Match Detection:** A match with at most  $k$  errors is found at position  $j$  if the  $m-1$  bit is set in any  $D_i$  (where  $i \leq k$ ).

## 4. Time and Space Complexity Analysis

Let  $n$  = text length,  $m$  = pattern length,  $\sigma$  = alphabet size, and  $k$  = number of errors.

Algorithm	Preprocessing Time	Search Time	Space
Shift-Or (Exact)	$O(m \cdot \sigma)$	$O(n)$	$O(\sigma)$
Shift-Or (Approx.)	$O(m \cdot \sigma)$	$O(k \cdot n)$	$O(k \cdot \sigma)$

**Analysis:**

- **Time:** The search time is linear  $O(n)$  for exact matching because each of the  $n$  text characters is processed with a few constant-time  $O(1)$  bitwise operations. For approximate matching, we do  $k$  such operations per character, leading to  $O(k \cdot n)$ .
- **Space:** Space is dominated by the bitmask table  $B$ , which stores one  $m$ -bit integer for each of the  $\sigma$  characters. For DNA,  $\sigma$  is a small constant (4), so preprocessing time is  $O(m)$  and space is  $O(1)$  (relative to  $n$ ).

## 5. Proof of Correctness (Exact Matching)

We prove by induction that the algorithm is correct.

**Invariant:** After processing text character  $T[j]$ , bit  $i$  in state vector  $D$  is 1 **if and only if**  $P[0...i] = T[j-i...j]$ .

**Base Case** ( $j = 0$ ):

- Initial state:  $D = 0$ .
- Update:  $D = ((0 \ll 1) \mid 1) \& B[T[0]] = 1 \& B[T[0]]$
- Bit 0 of  $D$  will be 1  $\iff$  Bit 0 of  $B[T[0]]$  is 1.
- Bit 0 of  $B[T[0]]$  is 1  $\iff P[0] = T[0]$ .
- Thus, the invariant holds for  $i=0$ .

**Inductive Step:** Assume the invariant holds after processing  $T[j-1]$ . Let this state be  $prev\_D$ . We must show it holds for  $T[j]$ .

- New state:  $D = ((prev\_D \ll 1) \mid 1) \& B[T[j]]$
- Consider bit  $i$  in the new  $D$ . For it to be 1:
  1. Bit  $i$  of  $B[T[j]]$  must be 1. This means  $P[i] = T[j]$ .
  2. Bit  $i$  of  $(prev\_D \ll 1) \mid 1$  must be 1.
    - If  $i > 0$ , this requires bit  $i-1$  of  $prev\_D$  to be 1.
    - By the hypothesis, bit  $i-1$  of  $prev\_D = 1 \iff P[0...i-1] = T[j-1-(i-1)...j-1]$  (i.e.,  $P[0...i-1] = T[j-i...j-1]$ ).
- Combining (1) and (2): Bit  $i$  of  $D$  is 1  $\iff (P[i] = T[j]) \text{ AND } (P[0...i-1] = T[j-i...j-1])$ .
- This is true  $\iff P[0...i] = T[j-i...j]$ .
- The invariant holds.

**Conclusion:** A match is detected when bit  $m-1$  is 1. By the invariant, this means  $P[0...m-1] = T[j-(m-1)...j]$ , which is the definition of a full pattern match ending at  $j$ .

## 6. Pseudo Code

### 6.1 Exact Matching

```
python function ShiftOrExact(text T, pattern P): m = length(P) n = length(T)
```

```

# --- Preprocessing ---
B = {} # Bitmask table
for c in alphabet:
    B[c] = 0

for i from 0 to m-1:
    B[P[i]] = B[P[i]] | (1 << i) # Set bit i for character P[i]

# --- Searching ---
D = 0 # State vector
matches = []

match_bit = 1 << (m-1) # Bit to check for a full match

for j from 0 to n-1:
    D = ((D << 1) | 1) & B[T[j]]

    if (D & match_bit) != 0:
        matches.append(j - m + 1) # Store start position

return matches

```

## 6.2 Approximate Matching (k errors)

function ShiftOrApproximate(text T, pattern P, k): m = length(P) n = length(T)

```

# --- Preprocessing (same as exact) ---
B = {}
for c in alphabet: B[c] = 0
for i from 0 to m-1: B[P[i]] = B[P[i]] | (1 << i)

# --- Searching ---
# D[i] stores state for exactly i errors
D = array[k+1] filled with 0

matches = []
match_bit = 1 << (m-1)

for j from 0 to n-1:
    prev_D = copy(D) # Store state from text char j-1

    # Update D[0] (0 errors)
    D[0] = ((prev_D[0] << 1) | 1) & B[T[j]]

    # Update D[1]...D[k]
    for i from 1 to k:
        # 1. Substitution (or match) on prev i-error state
        sub = ((prev_D[i] << 1) | 1) & B[T[j]]
        # 2. Deletion on prev (i-1)-error state
        del = (prev_D[i-1] << 1) | 1
        # 3. Insertion on prev (i-1)-error state
        ins = prev_D[i-1]
        # 4. Match on prev (i-1)-error state
        mat = (prev_D[i-1] << 1) & B[T[j]]

        D[i] = sub | del | ins | mat

    # Check for a match with at most k errors
    if (D[k] & match_bit) != 0:
        matches.append(j - m + 1)

# De-duplicate or refine match positions as needed
return unique(matches)

```

## 7. Dry Run: Exact Matching on DNA

Text (T): AACGT Pattern (P): ACG ( $m = 3$ )

### Step 1: Preprocessing

- $P[0] = 'A', P[1] = 'C', P[2] = 'G'$
- $B['A'] = 001$
- $B['C'] = 010$
- $B['G'] = 100$
- $B['T'] = 000$
- $match\_bit = 1 \ll (3-1) = 100$

### Step 2: Searching

D is initialized to 000.

j	T[j]	D (before)	(D << 1)   1	B[T[j]]	D (after)	D & 100 ?
0	'A'	000	001	001 (B['A'])	001	000 (No)
1	'A'	001	011	001 (B['A'])	001	000 (No)
2	'C'	001	011	010 (B['C'])	010	000 (No)
3	'G'	010	101	100 (B['G'])	100	100 (Yes!)
4	'T'	100	001 *	000 (B['T'])	000	000 (No)

(At  $j=4$ ,  $D \ll 1 = 1000$ . The high bit is lost, so  $000 \cdot 000 \mid 1 = 001$ )

Result: Match found at  $j=3$ . Starting position =  $j - m + 1 = 3 - 3 + 1 = 1$ . The match is  $T[1 \dots 3] = \text{"ACG"}$ . This is correct.

## 8. Situational Performance (On DNA Sequences)

### 8.1 Strengths

1. **Extreme Speed for Short Patterns:** For patterns where  $m \leq 64$ , the  $O(n)$  or  $O(k \cdot n)$  time complexity combined with extremely low-constant-factor bitwise operations makes Shift-Or one of the fastest algorithms available.
2. **Ideal for DNA's Small Alphabet:** The  $O(m \cdot \sigma)$  preprocessing is trivial for DNA where  $\sigma=4$ .
3. **Built-in Approximate Matching:** The extension to  $k$  errors is natural and efficient, making it perfect for finding DNA motifs that may contain small mutations (SNPs) or sequencing errors.
4. **Simplicity:** The exact-match algorithm is remarkably simple to implement.

### 8.2 Weaknesses (Major Performance Issues)

1. **Hard Pattern Length Limit:** The algorithm's primary weakness. Its performance relies on the pattern length  $m$  fitting into a single machine word (e.g., 64 bits).
  - If  $m > 64$ , the implementation becomes vastly more complex, requiring an *array* of integers for the state vector and masks, and all  $O(1)$  bitwise operations become  $O(m/w)$  (where  $w$  is word size).
  - This "multi-word" Shift-Or loses its core speed advantage and is much slower than algorithms like KMP or Boyer-Moore for long patterns.
2. **Biologically Naive Scoring:** Like Levenshtein, the  $k$ -errors adaptation is biologically naive. It treats all operations (substitutions, insertions, deletions) as having an equal cost of 1.
  - It cannot distinguish between a biologically common transition ( $A \rightarrow G$ ) and a rare transversion ( $A \rightarrow T$ ).
  - It cannot use **affine gap penalties** (e.g., a single 10-base-pair deletion is 1 event, not 10 edits).
3. **Not for Large Genomes:** The algorithm is  $O(n)$ , which is theoretically optimal. However, for searching a 3-billion-base-pair human genome,  $O(n)$  is still too slow. This is why genomics relies on *sub-linear* heuristic (BLAST) or indexed (BWA/Bowtie) algorithms.

**Conclusion:** Shift-Or is an excellent choice for a specific bioinformatics task: **repeatedly searching for many *short* (e.g., < 64bp) motifs, like transcription factor binding sites or primer sequences, within a medium-sized text (like a bacterial genome or a single gene region), especially when a small number of mismatches ( $k$ ) must be tolerated.**

## 9. References

- Baeza-Yates, R., & Gonnet, G. H. (1992). A new approach to text searching. *Communications of the ACM*, 35(10).
- Wu, S., & Manber, U. (1992). Fast text searching allowing errors. *Communications of the ACM*, 35(10).