FastCDC: a Fast and Efficient Content-Defined Chunking Approach for Data Deduplication

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Abstract
Content-Defined Chunking (CDC) has been playing a key role in data deduplication systems in the past 15 years or so due to its high redundancy detection ability. However, existing CDC-based approaches introduce heavy CPU overhead because they declare the chunk cut-points by computing and judging the rolling hashes of the data stream byte by byte. In this paper, we propose FastCDC, a Fast and efficient CDC approach, that builds and improves on the latest Gear-based CDC approach, one of the fastest CDC methods to our knowledge. The key idea behind FastCDC is the combined use of three key techniques, namely, simplifying and enhancing the hash judgment to address our observed challenges facing Gear-based CDC, skipping sub-minimum chunk cut-point to further speed up CDC, and normalizing the chunk-size distribution in a small specified region to address the problem of the decreased deduplication ratio stemming from the cut-point skipping. Our evaluation results show that, by using a combination of the three techniques, FastCDC is about 10× faster than the best of open-source Rabin-based CDC, and about 3× faster than the state-of-the-art Gear- and AE-based CDC, while achieving nearly the same deduplication ratio as the classic Rabin-based approach.

1 Introduction
Data deduplication, an efficient approach to data reduction, has gained increasing attention and popularity in large-scale storage systems due to the explosive growth of digital data. It eliminates redundant data at the file- or chunk-level and identifies duplicate contents by their cryptographically secure hash signatures (e.g., SHA1 fingerprint). According to deduplication studies conducted by Microsoft [12, 23] and EMC [30, 33], about 50% and 85% of the data in their production primary and secondary storage systems, respectively, are redundant and could be removed by the deduplication technology.

In general, chunk-level deduplication is more popular than file-level deduplication because it identifies and removes redundancy at a finer granularity. For chunk-level deduplication, the simplest chunking approach is to cut the file or data stream into equal, fixed-size chunks, referred to as Fixed-Size Chunking (FSC) [27]. Content-Defined Chunking (CDC) based approaches are proposed to address the boundary-shift problem facing the FSC approach [25]. Specifically, CDC declares chunk boundaries based on the byte contents of the data stream instead of on the byte offset, as in FSC, and thus helps detect more redundancy for deduplication. According to some recent studies [12, 22, 23, 26], CDC-based deduplication approaches are able to detect about 10-20% more redundancy than the FSC approach.

Currently, the most popular CDC approaches determine chunk boundaries based on the Rabin fingerprints of the content, which we refer to as Rabin-based CDC [8, 11, 25, 28]. Rabin-based CDC is highly effective in duplicate detection but time-consuming, because it computes and judges (against a condition value) the Rabin fingerprints of the data stream byte by byte [11]. A recent study, called QuickSync [9], suggests that CDC is computationally expensive for deduplication based synchronization in mobile cloud storage. In order to speed up the CDC process, other hash algorithms have been proposed to replace the Rabin algorithm for CDC, such as SampeByte [1], Gear [38], and AE [40]. Meanwhile, the abundance of computation resources afforded by multicore and manycore processors [20, 37] or GPU processors [2, 5, 15] has been leveraged for acceleration.

Generally, CDC consists of two distinctive and sequential stages: (1) hashing in which fingerprints of the data contents are generated and (2) hash judgment in which fingerprints are compared against a given value to identify and declare chunk cut-points. Our previous study of delta compression, Ddelta [38], suggests that the Gear hash (i.e., fp = (fp << 1) + G(b), see Section 3) is very efficient as a rolling hash for CDC. To the best of our knowledge, Gear appears to be one of the fastest rolling hash algorithms for CDC at present. However, according to our first observation from empirical and analytical studies, the Gear-based CDC has the potential problem of low deduplication ratio (i.e., the percentage of re-
dundant data reduced) stemming from its hash judgment stage where the sliding window size is very small. Meanwhile, our second observation indicates that the hash judgment stage becomes the new performance bottleneck during CDC after the fast Gear [38] is used in the hashing stage, because the accelerated hashing stage by Gear, has shifted the bottleneck to the hash judgment stage. Motivated by these two observations and the need to further accelerate the CDC process, we use an approach of enhancing and simplifying the hash judgment to further reduce the CPU operations during CDC.

Our third observation suggests that the predefined minimum chunk size used to avoid generating the very small-sized chunks (e.g., LBFS [25] employs the minimum chunk size of 2KB for Rabin-based CDC) can be employed for cut-point skipping during CDC, i.e., judiciously skipping some identified cut-points to eliminate the CDC operations in this region. Enlarging this minimum chunk size can further speed up the chunking process but at the cost of decreasing the deduplication ratio. This is because many chunks with skipped cut-points are not divided truly according to the data contents (i.e., content-defined). Thus, we propose a novel normalized Content-Defined chunking scheme, called normalized chunking, that normalizes the chunk-size distribution to a specified region that is guaranteed to be larger than the minimum chunk size to effectively address the problem facing the cut-point skipping approach.

Therefore, motivated by the above observations, we proposed FastCDC, a Fast and efficient CDC approach that combines the following three key techniques.

• **Simplified but enhanced hash judgment:** By padding several zero bits into the mask value for the hash-judging statement of the CDC algorithm to enlarge the sliding window size while using the fast Gear hash, FastCDC is able to achieve nearly the same deduplication ratio as the Rabin-based CDC; By further simplifying and optimizing the hash-judging statement, FastCDC minimizes the CPU overhead for the hash judgment stage in CDC.

• **Sub-minimum chunk cut-point skipping:** Our large scale study suggests that skipping the predefined minimum chunk size (used for avoiding small-sized chunks) increases the chunking speed but decreases the deduplication ratio (about 15% decline in the worst case). This motivates us to further enlarge the minimum chunk size to maximize chunking speed while developing a counter measure for the decreased deduplication ratio in the following normalized chunking approach.

• **Normalized chunking:** By selectively changing the number of mask bits ‘1’ in the hash-judging statement of CDC, FastCDC normalizes the chunk-size distribution to a small specified region (e.g., 8KB~16KB), i.e., the vast majority of the generated chunks fall into this size range, and thus minimizes the number of chunks of either too small or large in size. The benefits are twofold. First, it increases the deduplication ratio by reducing the number of large-sized chunks. Second, it reduces the number of small-sized chunks, which makes it possible to combine with the cut-point skipping technique above to maximize the CDC speed while without sacrificing the deduplication ratio.

Our evaluation results from a large-scale empirical study of CDC, based on seven datasets, demonstrate that FastCDC is about 10× faster than the Rabin-based CDC, and 3× faster than the state-of-the-art Gear- and AE-based CDC, while ensuring a high deduplication ratio.

The rest of the paper is organized as follows. Section 2 presents the necessary background for this research. Section 3 discusses our key observations that motivate the design of FastCDC. Section 4 describes the three key approaches used in FastCDC. Section 5 presents and discusses our experimental evaluation of FastCDC. Section 6 draws conclusions and outlines our future work.

## 2 Background

Chunking is the first critical step in the operational path of data deduplication, in which a file or data stream is divided into small chunks so that each can be duplicate-identified. Fixed-Size Chunking (FSC) [27] is simple and fast but may face the problem of low deduplication ratio that stems from the boundary-shift problem [25, 40]. For example, if one or several bytes are inserted at the beginning of a file, all current chunk cutpoints (i.e., boundaries) declared by FSC will be shifted and no duplicate chunks will be detected.

Content-Defined Chunking (CDC) is proposed to solve the boundary-shift problem. CDC uses a sliding-window technique on the content of files and computes a hash value (e.g., Rabin fingerprint [25, 28]) of the window. A chunk cut-point is declared if the hash value satisfies some pre-defined condition. As shown in Figure 1, to chunk a file \( V \) that is modified from the file \( V_1 \), the CDC algorithm can still identify the correct boundary of chunks \( C_1, C_3, \) and \( C_4 \), whose contents have not been modified. As a result, CDC outperforms FSC in terms of deduplication ratio and has been widely used in backup [33, 42] and primary [12, 23] storage systems.

Although the widely used Rabin-based CDC helps obtain a high deduplication ratio, it incurs heavy CPU overhead [2, 5, 9, 37]. Specifically, in Rabin-based CDC, the Rabin hash for a sliding window containing the byte sequence \( B_1, B_2, ..., B_n \) is defined as a polynomial \( A(p) \):

\[
Rabin(B_1, B_2, ..., B_n) = A(p) = \left\{ \sum_{x=1}^{n} B_x p^{n-x} \right\} \mod D \tag{1}
\]
Figure 1: The sliding window technique for the CDC algorithm. The hash value of the sliding window, \( fp \), is computed via the Rabin algorithm (this is the hashing stage of CDC). If the lowest \( \log_2 D \) bits of the hash value matches a threshold value \( r \), i.e., \( fp \mod D = r \), this offset (i.e., the current position) is marked as a chunk cut-point (this is the hash-judging stage of CDC).

where \( D \) is the average chunk size and \( \alpha \) is the number of bytes in the sliding window. Rabin hash is a rolling hash algorithm since it is able to compute the hash in an iterative fashion, i.e., the current hash can be incrementally computed from the previous value as follows:

\[
Rabin(B_2, B_3, \ldots, B_{\alpha+1}) = (\{Rabin(B_1, \ldots, B_\alpha) - B_1P^{\alpha-1}\}p + B_{\alpha+1}) \mod S \tag{2}
\]

However, Rabin-based CDC is time-consuming because it computes and judges the hashes of the data stream byte by byte, which renders the chunking process a performance bottleneck in deduplication systems. There are many approaches to accelerating the CDC process for deduplication systems and they can be broadly classified as either algorithmic oriented or hardware oriented. We summarize below some of these approaches that represent the state of the art.

**Algorithmic-oriented CDC Optimizations.** Since the frequent computations of Rabin fingerprints for CDC are time-consuming, many alternatives to Rabin have been proposed to accelerate the CDC process \[1, 38, 40\]. SampleByte \[1\] is designed for providing fast chunking for fine-grained network redundancy elimination, usually eliminating duplicate chunks as small as 32-64 bytes. It uses one byte to declare a fingerprint for chunking, in contrast to Rabin that uses a sliding window, and skips \( \frac{1}{2} \) of the expected chunk size before chunking to avoid generating extremely small-sized strings or chunks (they called “avoid oversampling”). Gear \[38\] uses fewer operations to generate rolling hashes by means of a small random integer table to map the values of the byte contents, so as to achieve higher chunking throughput. AE \[40\] is a non-rolling-hash-based chunking algorithm that employs an asymmetric sliding window to identify extremums of data stream as cut-points, which reduces the computational overhead for CDC. Yu et al. \[39\] adjust the function for selecting chunk boundaries such that if weak conditions are not met, the sliding window can jump forward, avoiding unnecessary calculation steps.

**Hardware-oriented CDC Optimizations.** StoreGPU \[2, 15\] and Shredder \[5\] make full use of GPGPU’s computational power to accelerate popular compute-intensive primitives (i.e., chunking and fingerprinting) in data deduplication. P-Dedupe \[37\] pipelines deduplication tasks and then further parallelizes the sub-tasks of chunking and fingerprinting with multiple threads and thus achieves higher throughput.

It is noteworthy that there are other chunking approaches trying to achieve a higher deduplication ratio but introduce more computation overhead on top of the conventional CDC approach. TTTD \[13\] and Regression chunking \[12\] introduces one or more additional thresholds for chunking judgment, which leads to a higher probability of finding chunk boundaries and decreases the chunk size variance. MAXP \[3, 7, 32\] treats the extremes in a fixed-size region as cut-points, which also results in smaller chunk size variance. In addition, Bimodal chunking \[17\], Subchunk \[29\], and FBC \[21\] re-chunk the non-duplicate chunks into smaller ones to detect more redundancy.

For completeness and self-containment we briefly discuss other relevant deduplication issues here. A typical data deduplication system follows the workflow of chunking, fingerprinting, indexing, and storage management \[14, 19, 34, 42\]. The fingerprinting process computes the cryptographically secure hash signatures (e.g., SHA1) of data chunks, which is also a compute-intensive task but can be accelerated by certain pipelining or parallelizing techniques \[16, 36, 37\]. Indexing refers the process of identifying the identical fingerprints for checking duplicate chunks in large-scale storage systems, which has been well explored in many previous studies \[10, 14, 35, 42\]. Storage management refers to the storage and possible post-deduplication processing of the non-duplicate chunks and their metadata, including such processes as related to further compression \[38\], defragmentation \[18\], reliability \[4\], security \[41\], etc. In this paper, we focus on designing a very fast and efficient chunking approach for data deduplication.

### 3 Observation and Motivation

In this section, we elaborate on and analyze the most relevant state-of-the-art CDC approaches to gain useful insights and observations. Table 1 shows a comparison among the three rolling hash algorithms for CDC, namely, Rabin, Adler, and Gear, which suggests Gear uses far fewer calculation operations than Rabin and Adler, thus being a good rolling hash candidate for CDC.

A good hash function must have a uniform distribution of hash values regardless of the hashed content. As shown in Figure 2, Gear-based CDC achieves this in two key ways: (1) It employs an array of 256 random 64-bit integers to map the values of the byte contents in the sliding window (i.e., the calculated bytes, whose size is the
### Table 1: The hashing stage of the Rabin-, Adler-, and Gear-based CDC.

<table>
<thead>
<tr>
<th>Name</th>
<th>Pseudocode</th>
<th>Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rabin</td>
<td>( fp = ((fp \cdot U(a)) \ll &lt; s)\cdot T \cdot fp \gg N )</td>
<td>Slow</td>
</tr>
<tr>
<td>Adler</td>
<td>( S_1 = A(b); S_2 = S_1; fp = (S_2 &lt; 16)\cdot S_1 )</td>
<td>Slow</td>
</tr>
<tr>
<td>Gear</td>
<td>( fp = (fp &lt; 1) + G(b) )</td>
<td>Fast</td>
</tr>
</tbody>
</table>

Note: ‘fp’ represents the fingerprint of the sliding window.

### Figure 2: A schematic diagram of the Gear hash.

- The bit-width of the \( fp \).
- The addition (“+”) operation adds the new byte in the sliding window into Gear hashes while the left-shift (“\( \ll < \)”) operation helps strip away the last byte of the last sliding window (e.g., \( B_{i-1} \) in Figure 2).
- This is because, after the \( \ll < \)” and modulo operations, the last byte \( B_{i-1} \) will be calculated into the \( fp \) as the \( G[B_{i-1}] \ll < n \) \( mod \ 2^n \), which will be equal to zero. As a result, Gear generates uniformly distributed hash values by using only three operations (i.e., “+”, “\( \ll < \)”, and an array lookup), enabling it to move quickly through the data content for the purpose of CDC.

### Figure 3: Rabin-based CDC performance as a function of the minimum chunk size used for cut-points skipping before chunking.

- Figure 3 (a) indicates that setting the minimum chunk size for cut-point skipping at \( \frac{1}{4} \times 2 \times \) of the expected chunk size can effectively accelerate the CDC process.
- This approach decreases the deduplication ratio by about 20% (see Figure 3 (b)) since many chunks are not divided truly according to the data content.

### Limited sliding window size.

The traditional hash judgment for the Rabin-based CDC, as shown in Figure 1 (i.e., "\( fp \ mod \ D = r' \)"), is also used by the Gear-based CDC [38]. But this results in a smaller sized sliding window used by Gear-based CDC since it uses Gear hash for chunking. As shown in Figure 5, the sliding window size of the Gear-based CDC will be equal to the number of the bits used by the mask value. Therefore, when using a mask value of \( 2^{13} \) for the expected chunk size of 8KB, the sliding window for the Gear-based CDC would be 13 bytes while that of the Rabin-based CDC would be 48 bytes [25].

### The time-consuming hash judgment.

**The time-consuming hash judgment.** Our implemen-
there are three metrics for evaluating CDC performance, namely, deduplication ratio, chunking speed, and the average generated chunk size. Note that the average generated chunk size may be nearly equal to or larger than the predefined expected chunk size (e.g., 8KB) due to factors such as the detailed CDC methods and datasets. This is also an important CDC performance metric because it reflects the metadata overhead for deduplication indexing, i.e., the larger the generated chunk size is, the fewer the number of chunks and thus the less metadata will be processed by data deduplication. However, it is difficult, if not impossible, to improve these three performance metrics simultaneously because they can be conflicting goals. For example, a smaller average generated chunk size leads to a higher deduplication ratio, but at the cost of lower chunking speed and high metadata overheads. Thus, FastCDC is designed to strike a sensible tradeoff among these three metrics so as to strive for high performance CDC, by using a combination of the three techniques with their complementary features as shown in Figure 4.

- Optimizing hash judgment: using a zero-padding scheme and a simplified hash-judging statement to speed up CDC without compromising the deduplication ratio, as detailed in Section 4.2.
- Sub-minimum chunk cut-point skipping: enlarging the predefined minimum chunk size and skipping cut-points for chunks smaller than that to provide a higher chunking speed and a larger average generated chunk size, as detailed in Section 4.3.
- Normalized chunking: selectively changing the number of mask ‘1’ bits for the hash judgment to approximately normalize the chunk-size distribution to a small specified region that is just larger than the predefined minimum chunk size, ensuring both a higher deduplication ratio and higher chunking speed, as detailed in Section 4.4.

In general, the key idea behind FastCDC is the combined use of the above three key techniques on top of Gear-based CDC, especially employing normalized chunking to address the problem of decreased deduplication ratio facing the cut-point skipping, and thus achieve high performance CDC on the three key metrics.

<table>
<thead>
<tr>
<th>FastCDC</th>
<th>High Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimizing Hash Judgment</td>
<td>HDR: High Deduplication Ratio</td>
</tr>
<tr>
<td>Cut-points Skipping</td>
<td>HCS: High Chunking Speed</td>
</tr>
<tr>
<td>Normalized Chunking</td>
<td>LCS: Large Avg. Chunk Size</td>
</tr>
</tbody>
</table>

Figure 4: The three key techniques used in FastCDC and their corresponding benefits for high performance CDC.

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4.2 Optimizing Hash Judgment

In this subsection, we propose an enhanced but simplified hash-judging statement to accelerate the hash judgment stage of FastCDC to further accelerate the chunking process on top of the Gear-based CDC and increase the deduplication ratio to reach that of the Rabin-based CDC. More specifically, FastCDC incorporates two main optimizations as elaborated below.

Enlarging the sliding window size by zero padding. As discussed in Section 3, the Gear-based CDC employs the same conventional hash judgment used in the Rabin-based CDC, where a certain number of the lowest bits of the fingerprint are used to declare the chunk cut-point, leading to a shortened sliding window for the Gear-based CDC (see Figure 5) because of the unique feature of the Gear hash. To address this problem, FastCDC enlarges the sliding window size by padding a number of zero bits into the mask value for hash judgment, the size of the sliding window used in FastCDC is enlarged to about 5+y bytes, where y=5 in this example.

(2) Hash judgment: \( fp \ & 0x001f == r ? \)

Figure 5: An example of the sliding window technique used in the Gear-based CDC. Here CDC consists of two stages: hashing and hash judgment. The size of the sliding window used for hash judgment is only 5 bytes because of the computation principles of the Gear hash.

(2) Hash judgment: \( fp \ & 0x02f0 == r ? \)

Figure 6: An example of the sliding window technique proposed for FastCDC. By padding \( y \) zero bits into the mask value for hash judgment, the size of the sliding window used in FastCDC is enlarged to about 5+y bytes, where \( y=5 \) in this example.

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Problem of decreased deduplication ratio facing the cut-point skipping approach. Therefore, FastCDC’s hash judgment statement reduces the unnecessary comparison operation that compares “fp & Mask” and r, thus further speeds up the CDC process as verified in Section 5.2.

4.3 Cut-point Skipping

Most of CDC-based deduplication systems impose a limit of the maximum and minimum chunk sizes, to avoid the pathologies of generating many extremely large- or small-sized chunks by CDC [17, 19, 23–25, 29]. A common configuration of the average, minimum, and maximum parameters follows that used by LBFS [25], i.e., 8KB, 2KB, and 64KB. Our experimental observation and mathematical analysis suggest that the cumulative distribution of chunk size X in Rabin-based CDC approaches with an expected chunk size of 8 KB (without the maximum and minimum chunk size requirements) follows an exponential distribution as follows:

\[ P(X \leq x) = F(x) = (1 - e^{-\frac{x}{\text{Min. Size}}}), \quad x \geq 0. \]  

(3)

Note that this theoretical exponential distribution in Equation 3 is based on the assumption that the data content and Rabin hashes of contents (recall Equation 1 and Figure 1 for CDC) follow a uniform distribution. Equation 3 suggests that the value of the expected chunk size will be 8KB according to the exponential distribution.

Figure 7 shows a comparison between the actual chunk-size distribution of the real-world datasets after the Rabin-based CDC and the chunk-size distribution obtained by the mathematical analysis based on Equation 3, which indicates that the two are almost identical. According to Equation 3, the chunks smaller than 2KB and larger than 64KB would account for about 22.12% and 0.03% of the total number of chunks respectively. This means that imposing the maximum chunk size requirement only slightly hurts the deduplication ratio but skipping cut-points before chunking to avoid generating chunks smaller than the prescribed minimum chunk size, or called sub-minimum chunk cut-point skipping, will impact the deduplication ratio significantly as evidenced in Figure 3. This is because a significant portion of the chunks are not divided truly according to the data contents, but forced by this cut-point skipping.

Given FastCDC’s goal of maximizing the chunking speed, enlarging the minimum chunk size and skipping sub-minimum chunk cut-point will help FastCDC achieve a higher CDC speed by avoiding the operations for the hash calculation and judgment in the skipped region. This gain in speed, however, comes at the cost of reduced deduplication ratio. To address this problem, we will develop a normalized chunking approach, to be introduced in the next subsection.

It is worth noting that this cut-point skipping approach, by avoiding generating chunks smaller than the minimum chunk size, also helps increase the average generated chunk size. In fact, the average generated chunk size exceeds the expected chunk size by an amount equal to the minimum chunk size. This is because the \( F(x) \) in Equation 3 is changed to \( 1 - e^{-\frac{x + \text{Min. Size}}{\text{Max. Size}}} \) after cut-point skipping, thus the value of the expected chunk size becomes 8KB + minimum chunk size, which will be verified in Section 5.3. The speedup achieved by skipping the sub-minimum chunk cut-point can be estimated by \( 1 + \frac{\text{the minimum chunk size}}{\text{the expected chunk size}} \). The increased chunking speed comes from the eliminated computation on the skipped region, which will also be verified in Section 5.3.

4.4 Normalized Chunking

In this subsection, we propose a novel chunking approach, called normalized chunking, to solve the problem of decreased deduplication ratio facing the cut-point skipping approach.
Figure 8: A conceptual diagram of the normalized chunking combined with the subminimum chunk cut-point skipping. The dotted line shows a higher level of normalized chunking.

skipping approach. As shown in Figure 8, normalized chunking generates chunks whose sizes are normalized to a specified region centered at the expected chunk size. After normalized chunking, there are almost no chunks of size smaller than the minimum chunk size, which means that normalized chunking enables skipping cut-points for subminimum chunks to reduce the unnecessary chunking computation and thus speed up CDC.

In our implementation of normalized chunking, we selectively change the number of effective mask bits (i.e., the number of ‘1’ bits) for the hash-judging statement. For the traditional CDC approach with expected chunk size of 8KB (i.e., 213), 13 effective mask bits are used for hash judgment (e.g., \(fp \& 0x1fff==r\)). For normalized chunking, more than 13 effective mask bits are used for hash judgment (e.g., \(fp \& 0x7fff==r\)) when the current chunking position is smaller than 8KB, which makes it harder to generate chunks of size smaller than 8KB. On the other hand, fewer than 13 effective mask bits are used for hash judgment (e.g., \(fp \& 0x0fff==r\)) when the current chunking position is larger than 8KB, which makes it easier to generate chunks of size larger than 8KB. Therefore, by changing the number of ‘1’ bits in FastCDC, the chunk-size distribution will be approximately normalized to a specified region always larger than the minimum chunk size, instead of following the exponential distribution (see Figure 7).

Generally, there are three benefits or features of normalized chunking (NC):

- NC reduces the number of small-sized chunks, which makes it possible to combine it with the cut-point skipping approach to achieve high chunking speed without sacrificing the deduplication ratio as suggested in Figure 8.
- NC further improves the deduplication ratio by reducing the number of large-sized chunks, which compensates for the reduced deduplication ratio caused by reducing the number of small-sized chunks in FastCDC.
- The implementation of FastCDC does not add additional computing and comparing operations. It simply separates the hash judgment into two parts, before and after the expected chunk size.

Figure 9 shows the chunk-size distribution after normalized chunking in comparison with FastCDC without NC on the TAR dataset (whose workload characteristics are detailed in Table 2 in Section 5.1). The normalization levels 1, 2, 3 indicate that the normalized chunking uses the mask bits of (14, 12), (15, 11), (16, 10), respectively, where the first and the second integers in the parentheses indicate the numbers of effective mask bits used in the hash judgment before and after the expected chunk size (or normalized chunk size) of 8KB. Figure 9 suggests that the chunk-size distribution is a reasonably close approximation of the normal distribution centered on 8KB at the normalization level of 2 or 3.

As shown in Figure 9, there are only a very small number of chunks smaller than 2KB or 4KB after normalized chunking while FastCDC without NC has a large number of chunks smaller than 2KB or 4KB (consistent with the discussion in Section 4.3). Thus, when combining NC with the cut-point skipping to speed up the CDC process, only a very small portion of chunk cut-points will be skipped in FastCDC, leading to nearly the same deduplication ratio as the conventional CDC approaches without the minimum chunk size requirement. In addition, normalized chunking allows us to enlarge the minimum chunk size to maximize the chunking speed without sacrificing the deduplication ratio.

It is worth noting that the chunk-size distribution shown in Figure 9 is not truly normal distribution but an approximation of it. Figures 9 (c) and (d) shows a closer approximation of normal distribution of chunk size achieved by using the normalization levels 2 and
Algorithm 1: FastCDC8KB

<table>
<thead>
<tr>
<th>Input: data buffer, src; buffer length, n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output: chunks at breakpoint i</td>
</tr>
</tbody>
</table>

MaskS ← 0x0003590703530000LL; // 15 ‘1’ bits
MaskA ← 0x0000d90303530000LL; // 13 ‘1’ bits
MaskL ← 0x0000d9003530000LL; // 11 ‘1’ bits

MinSize ← 2KB; MaxSize ← 64KB;

fp ← 0; i ← MinSize; NormalSize ← 8KB;

if n ≤ MinSize then
  return n;
if n ≥ MaxSize then
  n ← MaxSize;
else if n ≤ NormalSize then
  NormalSize ← n;
for i < NormalSize; i++;
do
  fp ← !fp & MaskS;
  if !fp & MaskA then
    return i; //if the masked bits are all ‘0’
for i < n; i++;
do
  fp ← !fp & MaskL;
  if !fp & MaskS then
    return i; //if the masked bits are all ‘0’
return i;

3. Interestingly, the highest normalization level of NC would be equivalent to Fixed-Size Chunking (FSC), i.e., all the chunk sizes are normalized to be equal to the expected chunk size. Since FSC has a very low deduplication ratio but extremely high chunking speed, it means that there will be a “sweet spot” among the normalization level, deduplication ratio, and chunking speed, which will be studied and evaluated in Section 5.

4.5 Putting It All Together

To put things together and in perspective, Algorithm 1 describes FastCDC combining the three key techniques: optimizing hash judgment, cut-point skipping, and normalized chunking (with the expected chunk size of 8KB).

As shown in Algorithm 1, FastCDC uses normalized chunking to divide the chunking judgment into two loops with the optimized hash judgment. Note that FastCDC without normalized chunking is not shown here but can be easily implemented by using the new hash-judging statement “if fp & MaskA” where the MaskA is padded with 35 zero bits to enlarge the sliding window size to 48 bytes as that used in the Rabin-based CDC [25]. Note that MaskA, MaskS, and MaskL are three empirically derived values where the padded zero bits are almost evenly distributed for slightly higher deduplication ratio according to our large scale tests.

FastCDC implements normalized chunking by using mask value MaskS and MaskL to make the chunking judgment harder or easier (to generate chunks smaller or larger than the expected chunk size) when the current position is smaller or larger than the expected chunk size, respectively. And the number of ‘1’ bits in MaskS and MaskL can be changed for different normalization levels. The minimum chunk size used in Algorithm 1 is 2KB, which can be enlarged to 4KB or 8KB to further speed up the CDC process while combining with normalized chunking. Tuning the parameters of minimum chunk size and normalization level will be studied and evaluated in the next Section.

5 Performance Evaluation

5.1 Experimental Setup

Experimental Platform. To evaluate FastCDC, we implement a prototype of the data deduplication system on the Ubuntu 12.04.2 operating system running on a quad-core Intel i7-4770 processor at 3.4GHz, with a 16GB RAM. To better evaluate the chunking speed, another quad-core Intel i7-930 processor at 2.8GHz is also used for comparison.

Configurations for CDC and deduplication. Three CDC approaches, Rabin-, Gear-, and AE-based CDC, are used as the baselines for evaluating FastCDC. Rabin-based CDC is implemented based on the open-source project LBFS [25] (also used in many published studies [14, 22] or project [6]), where the sliding window size is configured to be 48 bytes. The Gear- and AE-based CDC schemes are implemented according to the algorithms described in their papers [38, 40], and we obtain performance results similar to and consistent with those reported in these papers. Here all the CDC approaches are configured with the maximum and minimum chunk sizes of 8× and 128× of the expected chunk size, the same as configured in LBFS [25]. The deduplication prototype consists of approximately 3000 lines of C code, which is compiled by GCC 4.7.3 with the “-O3” compiler option.

Table 2: Workload characteristics of the seven datasets used in the performance evaluation.

<table>
<thead>
<tr>
<th>Name</th>
<th>Size</th>
<th>Workload descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>TAR</td>
<td>19 GB</td>
<td>85 tarred files from the open source projects such as GCC, GDB, Emacs, etc.</td>
</tr>
<tr>
<td>LNX</td>
<td>105 GB</td>
<td>200 versions of Linux source code files.</td>
</tr>
<tr>
<td>WEB</td>
<td>36 GB</td>
<td>15 days’ snapshots of the website: news.sina.com, which are collected by crawling software wget with a maximum retrieval depth of 3.</td>
</tr>
<tr>
<td>VMA</td>
<td>117 GB</td>
<td>75 virtual machine images of different OS release versions, including CentOS, Fedora, Debian, etc.</td>
</tr>
<tr>
<td>VMB</td>
<td>1.9 TB</td>
<td>125 backups of an Ubuntu 12.04 virtual machine image in use by a research group.</td>
</tr>
<tr>
<td>RDB</td>
<td>1.1 TB</td>
<td>200 backups of the redis key-value store database.</td>
</tr>
<tr>
<td>SYN</td>
<td>1.4 TB</td>
<td>200 synthetic backups. The backup is simulated by the file create/delete/modify operations [31].</td>
</tr>
</tbody>
</table>

Performance Metrics of Interest. Chunking speed
A comparison among the Rabin-based CDC (RC), Gear-based CDC (GC), and FastCDC (FC) approaches in terms of the deduplication ratio and the average size of generated chunks, as a function of the expected chunk size.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>CDC</th>
<th>Expected Chunk Size of 4K (B)</th>
<th>Expected Chunk Size of 8K (B)</th>
<th>Expected Chunk Size of 16K (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TAR</td>
<td>RC</td>
<td>54.81%</td>
<td>5561</td>
<td>47.58%</td>
</tr>
<tr>
<td></td>
<td>GC</td>
<td>51.68%</td>
<td>6094 (+9.58%)</td>
<td>44.90%</td>
</tr>
<tr>
<td></td>
<td>FC</td>
<td>54.14%</td>
<td>5722 (+2.90%)</td>
<td>47.64%</td>
</tr>
<tr>
<td>LNX</td>
<td>RC</td>
<td>97.69%</td>
<td>3289</td>
<td>97.25%</td>
</tr>
<tr>
<td></td>
<td>GC</td>
<td>97.78%</td>
<td>3473 (-0.27%)</td>
<td>97.33%</td>
</tr>
<tr>
<td></td>
<td>FC</td>
<td>97.69%</td>
<td>3845 (+0.44%)</td>
<td>97.26%</td>
</tr>
<tr>
<td>WEB</td>
<td>RC</td>
<td>96.50%</td>
<td>5011</td>
<td>95.09%</td>
</tr>
<tr>
<td></td>
<td>GC</td>
<td>95.68%</td>
<td>7091 (+41.5%)</td>
<td>94.09%</td>
</tr>
<tr>
<td></td>
<td>FC</td>
<td>96.14%</td>
<td>5330 (+4.37%)</td>
<td>94.02%</td>
</tr>
<tr>
<td>VMA</td>
<td>RC</td>
<td>42.99%</td>
<td>6367</td>
<td>38.23%</td>
</tr>
<tr>
<td></td>
<td>GC</td>
<td>42.60%</td>
<td>5798 (-8.94%)</td>
<td>37.37%</td>
</tr>
<tr>
<td></td>
<td>FC</td>
<td>42.97%</td>
<td>6293 (-1.16%)</td>
<td>37.96%</td>
</tr>
<tr>
<td>VMB</td>
<td>RC</td>
<td>96.41%</td>
<td>5958</td>
<td>96.13%</td>
</tr>
<tr>
<td></td>
<td>GC</td>
<td>96.41%</td>
<td>5662 (-4.96%)</td>
<td>96.06%</td>
</tr>
<tr>
<td></td>
<td>FC</td>
<td>96.39%</td>
<td>6021 (+1.05%)</td>
<td>96.09%</td>
</tr>
<tr>
<td>RDB</td>
<td>RC</td>
<td>97.36%</td>
<td>5116</td>
<td>95.53%</td>
</tr>
<tr>
<td></td>
<td>GC</td>
<td>97.20%</td>
<td>5463 (+6.78%)</td>
<td>95.21%</td>
</tr>
<tr>
<td></td>
<td>FC</td>
<td>97.35%</td>
<td>5118 (+0.04%)</td>
<td>95.50%</td>
</tr>
<tr>
<td>SYN</td>
<td>RC</td>
<td>95.64%</td>
<td>5479</td>
<td>93.64%</td>
</tr>
<tr>
<td></td>
<td>GC</td>
<td>96.03%</td>
<td>5338 (-2.57%)</td>
<td>94.30%</td>
</tr>
<tr>
<td></td>
<td>FC</td>
<td>95.65%</td>
<td>5473 (+0.11%)</td>
<td>93.67%</td>
</tr>
</tbody>
</table>
thus is not shown in this table due to space limit.

In general, FastCDC achieves nearly the same deduplication ratio as the Rabin-based CDC regardless of the expected chunk size and workload, and the difference between them is only about ±0.1~1.4% as shown in the 3rd, 5th, 7th columns in Table 3. On the other hand, the Gear-based CDC has a much lower deduplication ratio on the datasets TAR, WEB, and VMA due to its limited sliding window size as discussed in Section 3.

For the metric of the average size of generated chunks, the difference between the Rabin-based CDC and FastCDC is smaller than ±0.1% on most of the datasets. For the datasets TAR and WEB, FastCDC has 1~7% larger average chunk size than Rabin-based CDC, which is acceptable since the larger average chunk size means fewer chunks and fingerprints for indexing in a deduplication system (without sacrificing deduplication ratio) [33]. But for the Gear-based CDC, the average chunk size differs significantly in some datasets while its deduplication ratio is still a bit lower than other CDC approaches due to its smaller sliding window size.

In summary, FastCDC achieves a chunking speed that is 5× higher than the Rabin-based CDC while satisfactorily solving the problem of low deduplication ratio facing the Gear-based CDC, as shown in Figure 10 and Table 3.

5.3 Evaluation of Cut-point Skipping

This subsection discusses the evaluation results of cut-point skipping technique. Figures 11 (a) and (b) show the impact of applying different minimum chunk sizes on the chunking speed of FastCDC. Since the chunking speed is not so sensitive to the workloads, we only show the three typical workloads in Figure 11. In general, cut-point skipping greatly accelerates the CDC process since the skipped region will not be hash-processed by CDC. The speedup of the FastCDC applying the minimum chunk sizes of 4KB and 2KB over the FastCDC without the constraint of the minimum chunk size (i.e., Min-0KB) is about 1.25× and 1.50× respectively, which is consistent with the equation 1 + \( \frac{1}{I+\text{the minimum chunk size}} \) as discussed in Section 4.3.

Figures 11 (c) and (d) show the impact of applying different minimum chunk sizes on the deduplication ratio and average generated chunk size of FastCDC. In general, deduplication ratio declines with the increase of the minimum chunk size applied in FastCDC, but not proportionally. For the metric of the average generated chunk size in FastCDC, it is approximately equal to the summation of the expected chunk size and the applied minimum chunk size. This means that the MIN-4KB solution has the average chunk size of \( 8+4=12 \) KB, leading to fewer chunks for fingerprints indexing in deduplication systems. Note that the increased portion of the average generated chunk size is not always equal to the size of the applied minimum chunk size, because the Rabin hashes of contents may not strictly follow the uniform distribution (as described in Equation 3 in Section 4.3) on some datasets.

In summary, the results shown in Figure 11 suggest that cut-point skipping helps obtain higher chunking speed and increase the average chunk size but at the cost of decreased deduplication ratio. The decreased deduplication ratio will be addressed by normalized chunking as evaluated in the next two subsections.

5.4 Evaluation of Normalized Chunking

In this subsection, we conduct a sensitivity study of normalized chunking (NC) on the TAR dataset, as shown in Figure 12. Here the expected chunk size of FastCDC without NC is 8KB and the normalized chunk size of FastCDC with NC is configured as the 4KB + minimum chunk size. The normalization levels 1, 2, 3 refer to the three pairs of numbers of effective mask bits (14, 12), (15, 11), (16, 10) respectively that normalized chunking applies when the chunking position is smaller or larger than the normalized (or expected) chunk size, as discussed in Section 4.4.

Figures 12 (a) and (b) suggest that normalized chunk-
the three key techniques: optimizing hash judgment, cut-performance of FastCDC with the combined capability of FastCDC

5.5 Comprehensive Evaluation of FastCDC

In this subsection, we comprehensively evaluate the performance of FastCDC with the combined capability of the three key techniques: optimizing hash judgment, cut-point skipping, and normalized chunking (using NC-2 as suggested by the last subsection). Four approaches are tested for evaluation: RC with Min2KB (or RC-MIN-2KB) is Rabin-based CDC used in LBFS [25]; FC with Min2KB (or FC-MIN-2KB) uses the techniques of optimizing hash judgment and cut-point skipping with a minimum chunk size of 2KB; FC-NC with Min4KB and FC-NC with Min8KB refer to FastCDC using all the three techniques with a minimum chunk size of 4KB and 8KB, respectively. To better evaluate the deduplication ratio, Fixed-Size Chunking (XC) is also tested using the average chunk size of 10KB.

Evaluation results in Table 4 suggest that FC with Min2KB achieves nearly the same deduplication ratio as Rabin-based approach. FC-NC with Min4KB achieves the highest deduplication ratio among the five approaches while Fixed-Size Chunking (XC) has the lowest deduplication ratio. Note that XC works well on the LNX, WEB, VMB datasets, because LNX and WEB datasets have many files smaller than the fixed-size chunk of 10KB (and thus the average generated chunk size also smaller than 10KB) and VMB has many structured backup data (and thus VMB is suitable for XC).

Table 5 shows that RC and FC with Min2KB and XC generate similar average chunk size while FC-NC with Min4KB has a slightly small average chunk size. But the approach of FC-NC with Min8KB has a much smaller average chunk size, which means that it generates fewer chunks and thus less metadata for deduplication processing. Meanwhile, FC-NC with Min8KB still achieves a comparable deduplication ratio, slightly lower than RC as shown in Table 4, while providing a much higher performance.
chunking speed as discussed later.

Figure 13 suggests that FC-NC with Min8KB has the highest chunking speed, about 10× faster than the Rabin-based approach, about 2× faster than FC with Min2KB. This is because FC-NC with Min8KB is the final FastCDC using all the three techniques to speed up the CDC process. In addition, FC-NC with Min4KB is also a good CDC candidate since it has the highest deduplication ratio while also working well on the other two metrics of chunking speed and the average generated chunk size. Note that XC is not shown here because it has almost no computation overhead for chunking.

Table 6 further studies the CPU overhead among the four CDC approaches. The CPU overhead is averaged on 1000 test runs by the Linux tool “Perf”. The results suggest that FC-NC-MIN-8KB has the fewest instructions for CDC computation, the highest IPC (instructions per cycle), and thus the least CPU time overhead, i.e., CPU cycles. Generally, FastCDC greatly reduces the number of instructions for CDC computation by using the techniques of Gear-based hashing and optimizing hash judgment (i.e., “FC-MIN-2KB”), and then minimizes the number of computation instructions by enlarging the minimum chunk size for cut-point skipping and combining normalized chunking (i.e., “FC-NC-MIN-8KB”). In addition, FastCDC increases the IPC for the CDC computation by well pipelining the instructions of hashing and hash-judging tasks in up-to-date processors. Therefore, these results explain why FastCDC is about 10× faster than Rabin-based CDC is that the former not only reduces the number of instructions, but also increases the IPC for the CDC process.

In summary, as shown in Tables 4, 5, 6 and Figure 13, FastCDC (i.e., FC-NC-MIN-8KB) significantly speeds up the chunking process and achieves a comparable deduplication ratio while reducing the number of generated chunks by using a combination of the three key techniques proposed in Section 4.

6 Conclusion and Future Work

In this paper, we propose FastCDC, a much faster CDC approach for data deduplication than the state-of-the-art CDC approaches while achieving a comparable deduplication ratio. The main idea behind FastCDC is the combined use of three key techniques, namely, optimizing the hash judgment for chunking, subminimum chunk cut-point skipping, and normalized chunking. Our experimental evaluation demonstrates that FastCDC obtains a chunking speed that is about 10× higher than that of the Rabin-based CDC and about 3× that of the Gear- and AE-based CDC while achieving nearly the same deduplication ratio as the Rabin-based CDC.

In our future work, we plan to incorporate FastCDC in some other deduplication systems that are sensitive to the CPU overhead of content-defined chunking, such as QuickSync [9], to further explore the potentials and benefits of FastCDC. We also plan to release the FastCDC source code to be shared with the deduplication and storage systems research community.

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