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Abstract—Detecting symmetries is crucial to logic synthesis, technology mapping, detecting function equivalence under unknown input correspondence, and ROBDD minimization. State-of-the-art is represented by Mishchenko’s algorithm. In this paper we present an efficient anytime algorithm for detecting symmetries in Boolean functions represented as ROBDDs, that output pairs of symmetric variables until a prescribed time bound is exceeded. The algorithm is complete in that given sufficient time it is guaranteed to find all symmetric pairs. The complexity of this algorithm is in \( O(n^4 + n|G| + |G|^3) \) where \( n \) is the number of variables and \( |G| \) the number of nodes in the ROBDD, and it is thus competitive with Mishchenko’s \( O(|G|^3) \) algorithm in the worst-case since \( n \ll |G| \). However, our algorithm performs significantly better because the anytime approach only requires lightweight data structure support and it offers unique opportunities for optimization.

I. INTRODUCTION

Symmetry detection has been important since the days of Shannon [1] who observed that symmetric functions have particularly efficient switch network implementations. Symmetry detection is no less important today and knowledge of symmetric variables has many applications in logic synthesis [2,3], technology mapping [4,5], ROBDD minimization [6,7] and detecting equivalence of Boolean functions for which input correspondence is unknown [8,9].

The challenge in symmetry detection is to find efficient algorithms for detecting all symmetric variable pairs \((x_i, x_j)\) of a given Boolean function \(f(x_1 \ldots x_n)\), that is, find all pairs \((x_i, x_j)\) such that \(f(x_1 \ldots x_i \ldots x_j \ldots) = f(x_1 \ldots x_j \ldots x_i \ldots)\). The intuition being that \(f\) remains unchanged under the switching of the variables \(x_i\) and \(x_j\). This symmetry is formally known as the first-order classical symmetry, or the non-skew non-equivalence symmetry [10]. It can be shown from Boole’s expansion theorem [11] this is equivalent to checking equality of the co-factor pair \(f|_{x_i \ldots 0, x_j \ldots 1} = f|_{x_i \ldots 1, x_j \ldots 0}\). This formulation shows that it is possible to find all of the symmetric pairs by calling the co-factoring operation no more than \(n^2 - n\) times, where \(n\) is the number of variables. Early work on detecting symmetric variables in Boolean functions has focussed on the computation of these co-factor pairs and symmetry detected by checking their equivalence [12]. The use of ROBDDs to represent Boolean functions enables co-factor equivalence to be checked in constant time, however, repeated co-factoring involves the creation and deletion of many intermediate ROBDD nodes and for very large ROBDDs this overhead can be prohibitive. This method is often referred to as the naive method [12]. Möller, Mohrke and Weber [12] thus advocate the use of two preprocessing algorithms — two sieves — that detect pairs of asymmetric variables. These linear-time sieves significantly reduce the number of co-factor pairs that need to be computed. In general, however, the method still requires naïve co-factor computation, that is, it calls to the standard co-factoring algorithm the complexity of which is in \( O(|G| \log |G|) \) [13]. Methods that rely on symmetry sieves, such as those proposed in [7,12], are said to be based upon the so-called negative-thinking paradigm [14]. That is, they obtain the symmetric variable pairs from the set of all variable pairs by systematically removing all asymmetric variable pairs.

Because of the cost of repeated co-factoring, many symmetry detection methods endeavor to avoid naïve co-factor computation. Möller et al. [12] and Panda et al. [6] detect all symmetries between variables adjacent in the variable order with an algorithm in \( O(|G|) \). Rudell’s dynamic variable reordering algorithm [15] has also been used to detect symmetries, although the aim is not symmetry detection per se, but ROBDD minimization. Rudell’s algorithm considers each variable in turn moving it up and down in the variable ordering (subject to complexity limits) so as to minimize the ROBDD. Panda et al. [6] modify Rudell’s algorithm to detect symmetries between variables that become adjacent when one of the variables is repositioned in the ROBDD variable ordering. Symmetric variables are then grouped, and any subsequent reordering that is applied is required to preserve a contiguous variable ordering within each group. This approach to symmetry detection does not require naïve co-factor computation, but there is no guarantee that all symmetries will be found. State-of-the-art is represented by Mishchenko’s algorithm [14] that detects all symmetric variable pairs in a ROBDD in \( O(|G|^3) \). (Note that this algorithm is parameterized by the underlying set representation that is used to store the variable pairs, and therefore this complexity result does not consider the complexity of the set operations themselves. Most conservatively, assuming all set operations are linear, the overall running time is at least \( O(n^2|G|^3) \) since each set contains potentially \( O(n^2) \) elements). Algorithms such as those of Mishchenko [14] and Panda et al. [6] are based on the so-called positive-thinking paradigm [14]. That is they compute variable pairs that are symmetric, and in the case of Mishchenko’s algorithm, because of its completeness, those pairs not found to be symmetric are then known to be asymmetric.

The problem with existing symmetry detection methods is that they are either monolithic, inefficient, or incomplete. A monolithic algorithm has to be run to completion before it can return any answer; the value of such an algorithm is compromised if the running time is prohibitive. Mishchenko’s [14] algorithm falls into this class. Practically all engineering tasks (and logic synthesis is no exception) require an acceptable answer to be found in a reasonable amount of time rather than the optimal answer in an exorbitant amount of time. This is relevant in the context of symmetry detection because the running time of the state-of-the-art algorithm [14] can exceed 12 hours on some ROBDDs of less than a million nodes (actually this was benchmark \#mp12). This motivates the need for a so-called anytime algorithm that will incrementally detect pairs of symmetric variables until some given time bound is exceeded. Symmetry detection algorithms [7,12] based on naïve co-factor computation can be considered to be incremental but, alas, this approach is inefficient. The algorithm of Panda et al. [6] is an interesting example of an incremental algorithm that does not require co-factor computation but, unfortunately, the algorithm is incomplete for the purposes of symmetry detection.

In this paper we present a novel anytime algorithm for symmetry detection based on the negative-thinking paradigm, whose efficiency compares very favorably against that of Mishchenko in the case when all the pairs require to be enumerated. The algorithm demonstrates that, with careful construction, it is possible to detect symmetries incrementally without compromising efficiency. Our anytime algorithm is inspired by that of Mishchenko, but the correctness of our algorithm is surprisingly subtle in that it depends on paths not passing through...
given nodes in the ROBDD. For pedagogical purposes, two versions of
the algorithm are presented: a simple version that contains a minimal
number of components to ensure correctness; and a refined version that
demonstrates how an incremental algorithm has computational advan-
tages over a comparable monolithic algorithm. These two algorithms
are respectively presented in Sections III and IV. An intriguing aspect
of the anytime approach is that it permits transitivity to be fully ex-
ploded. It is well-known that if \((x_i, x_j), (x_j, x_k)\) are symmetric then
so is \((x_i, x_k)\) [16, 17], but this observation has had scant consideration
in the symmetry detection literature. Möller et al. [12, p. 681] state that
"we also use the fact that if \((x_i, x_j)\) and \((x_j, x_k)\) are pairs of
symmetric variables, then \((x_i, x_k)\) is a pair of symmetric variables
as well", seemingly missing the fact that if \((x_i, x_j)\) are symmetric
and \((x_i, x_k)\) are asymmetric then \((x_j, x_k)\) are asymmetric. Due
to the way our anytime algorithm decomposes symmetry detection into a
series of passes, one for each variable, we are free to apply asymme-
try/symmetry propagation between each of these passes to reduce the
expected cost of each pass. This is discussed in Section IV-C. Sec-
tions IV-A and IV-B show how the algorithm can be accelerated using
more well-known techniques that relate to adjacent symmetries [12]
and positive satisfy counts [8]. Extensive experimental results that are
given in Section V demonstrate the value of these re
and Section VI presents the concluding discussion. For clarity, we
summarize our contributions as follows:

- The paper presents a novel incremental, anytime algorithm for
  symmetry detection based on the negative-thinking paradigm.

- In theory, the algorithm is in \(O(n^4 + n |G| + |G|^2)\) where \(n < |G|
  \) (even considering the complexity of all set operations) which
compares favorably against state-of-the-art [14].

- The paper shows that an anytime algorithm can put low computa-
tional demands on the underlying data-structures that represent
pairs of symmetric variables. Thus anytime generality does not
have to sacrifice efficiency, indeed the converse is true.

- The paper explains how an incremental anytime approach offers
special opportunities for optimization, in that classical asym-
metry/symmetry sieves can precede the algorithm and asym-
metry/symmetry propagation techniques can be inserted into
the main loop of the algorithm.

- The paper also reports a hitherto overlooked subtlety of symme-
try detection: it seems that at least \(O(n |G|)\) preprocessing steps
must be performed before incremental symmetry detection may
commence. Rather surprisingly, the correctness of our algorithm
critically depends upon an \(O(n |G|)\) asymmetry sieve [12], that
relates to paths that can arise within an ROBDD in the presence
of symmetries. (As a consequence, we conjecture that there is no
way to construct an incremental, complete symmetry detection
algorithm without first applying preprocessing).

II. PRELIMINARIES

In this paper we consider completely specified Boolean functions
\(f : \{0, 1\}^n \rightarrow \{0, 1\}\) that are conventionally written as Boolean
formulæ defined over a variable set \(X = \{x_1, ..., x_n\}\). The
satisfy-count of an \(n\)-ary Boolean function \(f\) is defined as \(\|f\| = \|\{b_1, ..., b_n\} : f(b_1, ..., b_n) = 1\|\) [13]. The (Shannon) co-factor
of a function \(f\) w.r.t. a variable \(x_i\) and a Boolean constant \(b\) is defined
by \(f|_{x_i=b} = f(x_1, ..., x_{i-1}, b, x_{i+1}, ..., x_n)\). Multiple variable co-
factors can be defined inductively as \(f_0 = f, f_1 = f|_{x_1=b_1}\), and
\(f_{1\ldots1-b_1\ldots b_n} = f_0\). A function \(f\) over \(X\) is symmetric in a pair
of variables \((x_i, x_j)\) iff \(f|_{x_i=0, x_j=1..} = f|_{x_i=1, x_j=0..}\), otherwise it is
asymmetric in \((x_i, x_j)\). ROBDDs are obtained by inducing a total-order on \(X\). A BDD is a
rooted directed acyclic graph where each internal node is labeled with
a Boolean variable. Each internal node has one successor node con-
nected via an edge labeled 0, and another successor connected via an
edge labeled 1. Each external (leaf) node is either 0 or 1. The Boolean
function represented by a BDD can be evaluated for a given variable
assignment by traversing the graph from the root, taking the 1 edge at
a node when the variable is assigned to 1 and the 0 edge when the vari-
able is assigned to 0. The external node reached in this traversal indi-
cates the value of the Boolean function for the assignment. An OBBDD
is a BDD with the restriction that the label of a node is always less than
the label of any internal node reachable via its successors. An ROBDD
is an OBBDD with the additional constraint that the successors of any
internal node do not represent the same Boolean function. Note that
any internal node of an ROBDD is itself the root of an ROBDD. An
ROBDD \(f\) is symmetric in a pair of variables \((x_i, x_j)\) iff the Boolean
function it represents is symmetric in \((x_i, x_j)\). Finally, let \(|G|\) denote
the number of internal nodes in a ROBDD \(G\).

III. ANYTIME SYMMETRY DETECTION ALGORITHM

In this section we propose a novel, anytime approach to symme-
try detection. The algorithm presented in Algorithm 1 contains
the minimum number of components required so as to ensure correct-
ness. The algorithm takes as input an ROBDD \(f\) and returns the set
\(S\) of symmetric variable pairs. The algorithm is composed of two dis-
tinct procedures. ComputeAsymmetry(\(f\)) performs two depth-first
search (dfs) traversals over the ROBDD \(f\), to detect pairs of variables
that are asymmetric (in the particular sense that is described in Sec-
tion III-A). RemoveAsymmetry(\(f, i, C\)) filters a set of variables \(C\)
whose symmetry relationship with variable \(x_i\) is unknown to return
the set \(C' \subseteq C\) of variables that are symmetric with \(x_i\). (This procedure
is detailed in Section III-B).

Algorithm 1 ComputeSymmetricPairs(\(f\))

\[
A \leftarrow \text{ComputeAsymmetry}(f)
\]
\[
S \leftarrow \emptyset
\]
\[
\text{for } i = 1 \text{ to } n - 1 \text{ do}
\]
\[
G \leftarrow \{ j \mid (i, j) \notin (S \cup A) \land i < j \}
\]
\[
D \leftarrow \text{RemoveAsymmetry}(f, i, C)
\]
\[
S \leftarrow S \cup \{ (i, k), (k, i) \mid k \in D \}
\]
\[
A \leftarrow A \cup \{ (i, l), (l, i) \mid |C \cap D| \}
\]
\[
\text{return } S
\]

The call to ComputeAsymmetry initializes the set of asymmetric
variable pairs \(A\); \(S\) is initially empty. The remainder of the algorithm
calculates each of the \(n\) variables in turn. Firstly, a set \(C\) is constructed
that contains all variables whose symmetry relation with \(x_i\) has not yet
been ascertained. Secondly, the set of symmetric variables \(D\) returned
from RemoveAsymmetry is used to extend \(S\) and \(A\). Observe that
the sets \(S\) and \(A\) can be augmented in \(O(n)\) time when \(C\) and \(D\) are
represented as arrays. Furthermore, observe that \(C\) can be constructed
in \(O(n)\) time when the sets of pairs \(S\) and \(A\) are represented as adjac-
cency matrices. Finally, observe that actually only \(n - 1\) iterations of
the loop are required because of the structure of \(C\). Further details of
these two procedures are given in Sections III-A and III-B.

A. Computing Asymmetries

The algorithm that initializes \(A\) is constructed from lemmas
that detail how symmetric variables place structural constraints on
ROBDDs [12]. For completeness, we state these lemmas below:

Lemma 1. If an ROBDD \(f\) over a set of variables \(X = \{x_1, ..., x_n\}\)
is symmetric in the pair \((x_i, x_j)\) and \(i < j\), then every ROBDD rooted
at a node labeled \(x_i\) must contain a node labeled \(x_j\).

Lemma 2. If an ROBDD \(f\) over a set of variables \(X = \{x_1, ..., x_n\}\)
is symmetric in the pair \((x_i, x_j)\) and \(i < j\), then every path from the
root of \(f\) to a node labeled \(x_i\) must visit a node labeled \(x_j\).
Lemma 1 and Lemma 2 provide two conditions under which asymmetry can be observed. For any given node labeled $x_i$ we can compute the set of all variables $x_j$ that appear in an ROBDD that is rooted at that node, and any variable not appearing in this set is necessarily asymmetric with $x_i$. Furthermore, for any given node labeled $x_j$, we can compute the set of all variables $x_i$ that appear on all paths from the root of the ROBDD to the node, and any variable not appearing in this set is asymmetric with $x_j$. The asymmetry conditions of Lemma 1 and Lemma 2 can be checked in two DFS traversals of the ROBDD.

Algorithm 2 RemoveAsymmetry($f, i, C$)

```plaintext
if $C = \emptyset$ then
    return $\emptyset$

    $j \leftarrow \text{index}(f)$

    if $j > i \land f = \text{true} \lor f = \text{false}$ then
        return $C$
    else
        return RemoveAsymmetryVar($f[0], f[1], C$)
end if
```

The function $\text{index}(f)$ returns the index of the root node of $f$, that is, $i$ if the root is labeled $x_i$. The test $j > i$ implements a form of early termination: if the test is satisfied then the ROBDD $f$ can contain no node labeled $x_i$. The external nodes true and false also trigger early termination. At the heart of RemoveAsymmetry is a call to RemoveAsymmetryVar which encapsulates the logic to co-factor $f_0$ and $f_1$ so as to perform the symmetry check. The pseudocode for this procedure is given in Algorithm 3. Whenever the call RemoveAsymmetryVar is reached, it examines the co-factors of $f$ to remove variables from $C$ that are asymmetric w.r.t $x_i$. First, consider the case when both root nodes of $f_0$ and $f_1$ are labeled with the same variable $x_i$. In this case we compute $f_0|_{x_i=0}$ and $f_1|_{x_i=0}$ and check for equivalence. When, $f_0$ is labeled with $x_i$ and $f_1$ is labeled with $x_j$ where $j < k$, the check reduces to $f_0|_{x_i=1} = f_1$. Third, the $k < j$ case is analogous to the second. The recursive calls follow the co-factor check because it is necessary to check symmetry across all variable assignments. Note that both RemoveAsymmetry and RemoveAsymmetryVar terminate as soon as $C = \emptyset$.

When $C$ is implemented as an array, the complexity of a single call to RemoveAsymmetryVar is $O(|G|^2)$. This follows since co-factor comparison and $C \setminus \{i\}$ are in $O(1)$, as is the test $C = \emptyset$ when $C$ is augmented with a counter to record $|C|$. Overall, RemoveAsymmetryVar can only be invoked a total of $|G|$ times from within Algorithm 1, thus RemoveAsymmetryVar contributes $O(|G|^3)$ to the overall running time. The $n-1$ calls to RemoveAsymmetry cumulatively cost $O(n|G|)$.

**IV. OPTIMIZED ANYTIME SYMMETRY DETECTION ALGORITHM**

In this section we propose a series of optimizations for Algorithm 1. This refined algorithm retains the incremental nature of the original algorithm, and in fact shows how this can be exploited by several optimizations. These optimizations seek to reduce the size of the set $C$, and hence the running time of the call.
Algorithm 3 RemoveAsymmetryVar($f_0, f_1, C$)

if $C = \emptyset$ then
  return $\emptyset$
else
  if $(f_0 = \text{true} \lor f_0 = \text{false}) \land (f_1 = \text{true} \lor f_1 = \text{false})$ then
    return $C$
  else
    $j \leftarrow \text{index}(f_0)$
    $k \leftarrow \text{index}(f_1)$
    if $j = k$ then
      $(l, f_0, f_0, f_1, f_1) \leftarrow (j, f_0|_{j-0}, f_0|_{j-1}, f_1|_{k-0}, f_1|_{k-1})$
    else if $j < k$ then
      $(l, f_0, f_0, f_1, f_1) \leftarrow (j, f_0|_{j-0}, f_0|_{j-1}, f_1, f_1)$
    else
      $(l, f_0, f_0, f_1, f_1) \leftarrow (k, f_0, f_1|_{k-0}, f_1|_{k-1})$
    if $f_0 \neq f_1$ then
      $C \leftarrow C \setminus \{l\}$
  $C \leftarrow \text{RemoveAsymmetryVar}(f_0, f_1, C)$
  return $\text{RemoveAsymmetryVar}(f_0, f_1, C)$

RemoveAsymmetry($f, i, C$), by enriching the sets $A$ and $S$ on-the-fly, before and between, iterations of the main loop. The symmetry sieve algorithms presented by [7, 12] give a way to refine the sets $A$ and $S$ before the loop is entered. When the loop is entered, it is possible to take advantage of the transitivity of the symmetry relation to add further pairs to $A$ and $S$. The optimized symmetry detection algorithm presented in Algorithm 4 takes as input an ROBDD $f$ and returns the set $S$ of symmetric variable pairs. The new algorithm includes three additional procedures, namely, ComputeSatisfyCounts($f$), ComputeAdjSymmetry($f$) and SymmetryClosure($A, S$) which are detailed in Sections IV-A and IV-B, IV-C respectively.

Algorithm 4 OptimizedSymmetricPairs($f$)

$A \leftarrow \text{ComputeAsymmetry}(f)$

$M \leftarrow \text{ComputeSatisfyCounts}(f)$

for $i = 1$ to $n$ do
  for $j = i + 1$ to $n$ do
    if $M(i) \neq M(j)$ then
      $A \leftarrow A \cup \{(i, j), (j, i)\}$
    $S \leftarrow \text{ComputeAdjSymmetry}(f)$

for $i = 1$ to $n - 2$ do
  $(A, S) \leftarrow \text{SymmetryClosure}(A, S)$
  $C \leftarrow \{\{i, j\} \in (S \cup A) \setminus i + 1 < j\}$
  $D \leftarrow \text{RemoveAsymmetry}(f, i, C)$
  $S \leftarrow S \cup \{(i, k), (k, i) \mid k \in D\}$
  $A \leftarrow A \cup \{(i, l), (l, i) \mid l \in C \setminus D\}$
return $S$

ComputeSatisfyCounts($f$) returns a mapping $M$ from variable indices to a natural number that can be used to distinguish pairs of asymmetric variables, that is, if $M(i) \neq M(j)$ then $(x_i, x_j)$ are asymmetric. ComputeAdjSymmetry($f$) returns the set of symmetric variable pairs for those pairs that are adjacent in the ROBDD ordering (which permits the number of loop iterations to be relaxed to $n - 2$). Finally, SymmetryClosure($A, S$) takes as input two sets $A$ and $S$ of variable pairs known to be asymmetric and symmetric respectively. Two new sets $A' \supseteq A$ and $S' \supseteq S$ are output that are derived by exploiting the transitivity of symmetry.

A. Positive Satisfy-Counts

A consequence of symmetry, which can also be used to detect asymmetry [8], relates to the satisfy count of one positive co-factor of a variable to the satisfy count of another:

**Lemma 4.** If a Boolean function $f$ over a set of variables $X = \{x_1, \ldots, x_n\}$ is symmetric in the pair $(x_i, x_j)$, then $|f|_{x_i \leftarrow 1} = |f|_{x_j \leftarrow 1}$.

Computing the satisfy counts of all co-factors can be realized using a single dfs traversal of the ROBDD in $O(n|G|)$ time [8]. Finding the resultant asymmetries requires $n^2$ comparisons in Algorithm 4, and thus the overall complexity of this phase is $O(n^2 + n|G|)$.

B. Adjacent Symmetries

The following lemma details a special case of symmetry, which relates to variables that are adjacent in the ROBDD ordering:

**Lemma 5.** If a ROBDD $f$ over a set of variables $X = \{x_1, \ldots, x_n\}$ is symmetric in the pair $(x_i, x_{i+1})$ iff $g|_{x_i \leftarrow 0, x_{i+1} \leftarrow 1} = g|_{x_i \leftarrow 1, x_{i+1} \leftarrow 0}$ holds for each ROBDD $g$ that is rooted at a node labeled $x_i$.

This lemma leads to an $O(|G|)$ time algorithm that can detect all symmetry and asymmetry relationships between adjacent variables [12]. (In fact the algorithm of Moller et al. can be improved to detect asymmetry for a pair of non-adjacent variables, that is, a pair $(x_i, x_k)$ is asymmetric if there exists a node $g$ labeled $x_i$ with successor nodes labeled $x_k$ and $x_i$ where $i + 1 < k \leq l$ and $g|_{x_i \leftarrow 0, x_k \leftarrow 1} \neq g|_{x_i \leftarrow 1, x_k \leftarrow 0}$.)

C. Symmetry Propagation

The final lemma can be obtained by recalling that a function $f$ remains unchanged under the switching of any symmetric variables:

**Lemma 6.** If a Boolean function $f$ over a set of variables $X = \{x_1, \ldots, x_n\}$ is symmetric in the pairs $(x_i, x_j)$ and $(x_j, x_k)$ then $f$ is also symmetric in the pair $(x_i, x_k)$.

This transitivity result provides a way of enriching the set $S$, that is, if $(x_i, x_j), (x_j, x_k) \in S$ then it follows that $(x_i, x_k)$ is also a symmetric pair. Further, given $(x_i, x_j) \in S, (x_i, x_k) \in A$ then it follows that the pair $(x_j, x_k)$ is asymmetric, that is, $A$ can possibly be enriched too. This follows since if $(x_j, x_k)$ is symmetric then by the lemma it follows that $(x_i, x_k)$ is symmetric, which is a contradiction. Adding those variable pairs to $A$ and $S$ which can be inferred through transitivity is not dissimilar to computing the transitive closure of a binary relation. This motivates adapting the Floyd-Warshall [18, 19] all-pairs-shortest-path algorithm to this task by representing the sets of pairs $A$ and $S$ as an adjacency matrix of $n^2$ size. The pseudo-code for this algorithm is given in Algorithm 5.

Algorithm 5 SymmetryClosure($A, S$)

for $i = 1$ to $n$ do
  for $j = i + 1$ to $n$ do
    for $k = 1$ to $n$ do
      if $(k, i) \in S \land (k, j) \in S$ then
        $S \leftarrow S \cup \{(j, i), (i, j)\}$
      else if $(k, i) \in A \land (k, j) \in S$ then
        $A \leftarrow A \cup \{(j, i), (i, j)\}$
      else if $(k, i) \in S \land (k, j) \in A$ then
        $A \leftarrow A \cup \{(j, i), (i, j)\}$
    return $(A, S)$

The complexity of Algorithm 5 is in $O(n^3)$ since membership check and single element insertion can be performed in $O(1)$ time for an adjacency matrix representation. Note that although the worst-case running time is not dependent on the number of symmetries present, larger symmetry sets induce more propagation which reduces the overall running time.
TABLE I

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<th># Out</th>
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<th>read</th>
<th>naive</th>
<th>$\Sigma$ II</th>
<th>A</th>
<th>A+B</th>
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<td>21.80</td>
<td>&gt;7200</td>
<td>132.72</td>
<td>71.64</td>
<td>68.23</td>
<td>66.08</td>
</tr>
</tbody>
</table>

simp10 105 | 1 | 722074 | 19 | 58.45 | >7200 | 661.70 | 65.28 | 47.53 | 43.90 | 40.88 |

simp12 117 | 1 | 758330 | 23 | 76.23 | >7200 | >7200 | 105.67 | 61.94 | 59.87 | 57.59 |

simp14 120 | 1 | 562326 | 36 | 70.38 | >7200 | 1114.29 | 75.75 | 38.48 | 36.17 | 30.63 |

hom06 104 | 1 | 1176845 | 20 | 65.22 | >7200 | 274.90 | 115.66 | 91.70 | 88.31 | 81.50 |

hom08 95 | 1 | 893312 | 16 | 56.48 | >7200 | 135.79 | 67.79 | 54.99 | 50.89 | 49.00 |

hom10 130 | 1 | 309221 | 29 | 29.98 | >7200 | 1510.32 | 35.85 | 33.39 | 31.61 | 31.21 |

cal004 53 | 1 | 782640 | 2 | 5.40 | >7200 | 147.97 | 31.35 | 12.33 | 12.33 | 12.10 |

cal008 96 | 1 | 682617 | 16 | 20.40 | >7200 | 326.92 | 53.54 | 44.69 | 43.05 | 42.78 |

cal016 107 | 1 | 861209 | 26 | 60.10 | >7200 | 305.11 | 72.68 | 59.96 | 59.90 | 59.80 |

urquhart2_25 48 | 1 | 722657 | 5 | 3.06 | >7200 | 70.50 | 26.22 | 20.23 | 20.21 | 17.95 |

urquhart3_25 62 | 1 | 1771025 | 24 | 6.22 | >7200 | >7200 | 82.98 | 81.14 | 76.97 | 72.80 |

urquhart4_25 68 | 1 | 1736705 | 27 | 5.96 | >7200 | >7200 | 83.44 | 81.84 | 76.48 | 72.02 |

rope_00002 54 | 1 | 634914 | 3 | 3.06 | >7200 | 192.77 | 22.48 | 18.53 | 18.47 | 18.50 |

rope_00004 62 | 1 | 1052214 | 10 | 4.73 | >7200 | 487.26 | 41.71 | 39.70 | 37.90 | 37.82 |

cal006 61 | 1 | 759039 | 13 | 3.14 | >7200 | 657.74 | 35.78 | 30.76 | 30.64 | 30.68 |

urquhart7_25 111 | 1 | 290127 | 30 | 78.35 | >7200 | 95.15 | 30.10 | 29.56 | 23.21 | 22.99 |

urquhart8_25 116 | 1 | 539419 | 38 | 88.08 | >7200 | 1866.62 | 70.34 | 69.84 | 54.19 | 53.42 |

urquhart9_25 123 | 1 | 277291 | 36 | 47.96 | >7200 | 142.10 | 37.63 | 37.50 | 30.98 | 30.95 |

cal010 125 | 1 | 393485 | 28 | 69.08 | >7200 | 261.32 | 52.97 | 50.53 | 45.38 | 44.74 |

cal012 129 | 1 | 667877 | 43 | 50.95 | >7200 | 368.50 | 106.32 | 102.87 | 85.43 | 84.90 |

cal014 118 | 1 | 767735 | 40 | 47.29 | >7200 | 415.57 | 111.49 | 110.40 | 73.48 | 71.34 |

V. EXPERIMENTAL RESULTS

To assess the efficiency of the anytime approach, the algorithm, complete with all its refinements was implemented using the CUDD [20] Decision Diagram package. The rationale for this choice of library was that the Extra DD library [21], which implements Mishchenko’s algorithm, also uses CUDD. Experiments were performed on an UltraSPARC III 900MHz based system with 16GB RAM under the Solaris 9 Operating System. All programs in the CUDD package, the Extra library, and our algorithm — were compiled with the GNU C Compiler version 3.3.0 with -O3 enabled. The algorithms were run against a range of MCNC and ISCAS benchmark circuits of varying size [22], as well as several other benchmarks derived from the SAT literature. All timings were averaged over four runs and are given in seconds. Table I presents the results of these tests, the first four columns of Table I give the circuit name, number of inputs, outputs and the total number of nodes over all outputs respectively. Column five indicates the total number of all symmetric pairs found over each of the outputs of the circuit. Column six gives the time in seconds to read in the benchmark circuit and construct the ROBDD applying variable sifting. The remaining six columns give the runtimes required to compute all symmetric and asymmetric pairs. The first of these is the naive method for computing all co-factor pairs. The second is Mishchenko’s implementation of his own algorithm [21]. The third column is the unoptimized algorithm presented in Section III. The remaining three columns relate to the refinements presented in Section IV, that is, with the optimizations of Sections IV-A, IV-B and IV-C cumulatively enabled. The rationale for implementing the naive method was to verify the implementation of our algorithm and Mishchenko’s; the performance numbers are included to quantify the value of Mishchenko’s algorithm. Note, that these figures present Mishchenko’s algorithm in best light since when garbage collection is enabled the performance of Mishchenko’s implementation can degrade, presumably because of its extensive use of ZDDs [23] to represent sets. For example, the circuit pair requires 33.40s compared to 6.62s with garbage collection disabled. Enabling garbage collection has no perceivable impact on our algorithm.

Figure 2 illustrates the outcome of some experiments designed to explore the anytime nature of the algorithm. In these experiments, the optimized algorithm was stopped after progressively larger timeouts were exceeded. The graphs display the number of symmetries found against these timeouts. Future work will investigate whether reordering the iterations in the main loop, for example, choosing i with the largest number of unknowns, increases the proportion of symmetries found early in the search.

VI. DISCUSSION

This paper presents a novel anytime symmetry detection algorithm, that is capable of detecting all symmetric variable pairs. The startling speed-ups over Mishchenko’s algorithm stem from our use of a single static adjacency matrix rather than sets of pairs that are repeatedly generated. It is important to appreciate that there is no obvious way to re-engineer Mishchenko’s algorithm to use a static adjacency matrix. This is because Mishchenko’s algorithm is a bottom-up, divide and conquer algorithm that derives the solution to a problem by obtaining, and combining, the solutions to several sub-problems. Mishchenko [14, p 1590] points out that caching the answers to these sub-problems is required to reduce the computational complexity from exponential to polynomial yet this requires multiple data structures to be maintained. By contrast, the anytime approach merely has to mark nodes as visited in any of the ROBDD traversals. Moreover, the only set operations that the anytime algorithm require are atomic
\(O(1)\) insertions and deletions, which finesse the otherwise \(O(n^2)\) overhead of set intersection and union. This partly explains the speed of the anytime approach.

Another source of speedup, in the anytime approach, is its amenability to optimization by enriching the \(A\) and \(S\) sets on-the-fly. One would think that computing the transitive closure is prohibitively expensive, but close inspection of the SPARC assembler revealed that the GNU compiler was able to generate very tight code from the regular structure of the closure algorithm.

Finally, Mishchenko’s algorithm [14] is capable of detecting all four basic types of symmetry, namely, non-skew non-equivalence symmetry — the notion of symmetry considered in this paper — (NE), non-skew equivalence symmetry (E), skew equivalence symmetry (!E) and the skew non-equivalence symmetry (!NE). In this more general setting, a pair of variables are asymmetric if they do not satisfy any of these four symmetry types. A key component of our optimized algorithm, SymmetryClosure, can be straightforwardly generalized to infer these transitive symmetries by using a 4-bit encoding to indicate which symmetry types apply. A lookup-table of \((4^2) \times (4^2) = 256\) entries can then be used to obtain the transitive symmetry types without any impact on the asymptotic running time.

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REFERENCES


