Emulating round-to-nearest ties-to-zero "augmented" floating-point operations using round-to-nearest ties-to-even arithmetic

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Abstract—The 2019 version of the IEEE 754 Standard for Floating-Point Arithmetic recommends that new “augmented” operations should be provided for the binary formats. These operations use a new “rounding direction”: round-to-nearest ties-to-zero. We show how they can be implemented using the currently available operations, using round-to-nearest ties-to-even with a partial formal proof of correctness.

Keywords. Floating-point arithmetic, Numerical reproducibility, Rounding error analysis, Error-free transforms, Rounding mode, Formal proof.

I. INTRODUCTION AND NOTATION

The new IEEE 754-2019 Standard for Floating-Point (FP) Arithmetic [8] supersedes the 2008 version. It recommends that new “augmented” operations should be provided for the binary formats (see [15] for history and motivation). These operations are called augmentedAddition, augmentedSubtraction, and augmentedMultiplication. They use a new “rounding direction”: round-to-nearest ties-to-zero. The reason behind this recommendation is that these operations would significantly help to implement reproducible summation and dot product, using an algorithm due to Demmel, Ahrens, and NGuyen [5]. Obtaining very fast reproducible summation with that algorithm may require a direct hardware implementation of these operations. However, having these operations available on common processors will certainly take time, and they may not be available on all platforms. The purpose of this paper is to show that, in the meantime, one can emulate these operations with conventional FP operations (with the usual round-to-nearest ties-to-even rounding direction), with reasonable efficiency. In this paper, we present the first proposed emulation algorithms, with proof of their correctness and experimental results. This allows, for instance, the design of programs that use these operations, and that will be ready for use with full efficiency as soon as the augmented operations are available in hardware. Also, when these operations are available in hardware on some systems, this will improve the portability of programs using these operations by allowing them to still work (with degraded performance, however) on other systems.

In the following, we assume radix-2, precision-p floating-point arithmetic [13]. The minimum floating-point exponent is $e_{\text{min}} < 0$ and the maximum exponent is $e_{\text{max}}$. A floating-point number is a number of the form

$$x = M_x \times 2^{e_x - p + 1},$$

where $M_x$ is an integer satisfying $|M_x| \leq 2^p - 1$, $e_x \in [e_{\text{min}}, e_{\text{max}}]$, and $x$ is the round-to-nearest ties-to-zero. The reason behind this recommendation is that these operations would significantly help to implement reproducible summation and dot product, using an algorithm due to Demmel, Ahrens, and NGuyen [5]. Obtaining very fast reproducible summation with that algorithm may require a direct hardware implementation of these operations. However, having these operations available on common processors will certainly take time, and they may not be available on all platforms. The purpose of this paper is to show that, in the meantime, one can emulate these operations with conventional FP operations (with the usual round-to-nearest ties-to-even rounding direction), with reasonable efficiency. In this paper, we present the first proposed emulation algorithms, with proof of their correctness and experimental results. This allows, for instance, the design of programs that use these operations, and that will be ready for use with full efficiency as soon as the augmented operations are available in hardware. Also, when these operations are available in hardware on some systems, this will improve the portability of programs using these operations by allowing them to still work (with degraded performance, however) on other systems.

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This is illustrated in Fig. 1. As one can infer from the definitions, \( RN_e(t) \) and \( RN_0(t) \) can differ in only two circumstances (called halfway cases): when \( t \) is halfway between two consecutive floating-point numbers, and when \( t = \pm (\Omega + 2^{\max - p}) \).

![Fig. 1: Round-to-nearest ties-to-zero (assuming we are in the positive range). Number \( x \) is rounded to the (unique) FP number nearest to \( x \). Number \( y \) is a halfway case: it is exactly halfway between two consecutive FP numbers: it is rounded to the one that has the smallest magnitude.](image)

The augmented operations are required to behave as follows [8], [15]:

- **augmentedAddition** \((x, y)\) delivers \((a_0, b_0)\) such that \(a_0 = RN_0(x + y)\) and, when \(a_0 \notin \{-\infty, \text{NaN}\}, b_0 = (x+y) - a_0\). When \(b_0 = 0\), it is required to have the same sign as \(a_0\). One easily shows that \(b_0\) is a FP number. For special rules when \(a_0 \in \{-\infty, \text{NaN}\}\), see [15];

- **augmentedSubtraction** \((x, y)\) is exactly the same as augmentedAddition\((x, -y)\), so we will not discuss that operation further;

- **augmentedMultiplication** \((x, y)\) delivers \((a_0, b_0)\) such that \(a_0 = RN_0(x \cdot y)\) and, where \(a_0 \notin \{-\infty, \text{NaN}\}, b_0 = RN_0((x \cdot y) - a_0)\). When \((x \cdot y) - a_0 = 0\), the floating-point number \(b_0\) (equal to zero) is required to have the same sign as \(a_0\). Note that in some corner cases (an example is given in Section IV-A), \(b_0\) may differ from \((x \cdot y) - a_0\) (in other words, \((x \cdot y) - a_0\) is not always a floating-point number). Again, rules for handling infinities, NaNs and the signs of zeroes are given in [8], [15].

Because of the different rounding function, these augmented operations differ from the well-known Fast2Sum, 2Sum, and Fast2Mult algorithms (Algorithms 1, 2 and 3 below). As said above, the goal of this paper is to show that one can implement these augmented operations just by using rounded-to-nearest ties-to-even FP operations and with reasonable efficiency on a system compliant with IEEE 754-2008.

Let \( t \) be the exact sum \( x + y \) (if we consider implementing augmentedAddition) or the exact product \( x \cdot y \) for augmentedMultiplication. To implement the augmented operations, in the general case (i.e., the sum or product does not overflow, and in the case of augmentedMultiplication, \( x \) and \( y \) satisfy the requirements of Lemma 2 below), we first use the classical Fast2Sum, 2Sum, or Fast2Mult algorithms to generate two FP numbers \( a_e \) and \( b_e \) such that \( a_e = RN_e(t) \) and \( b_e = t - a_e \). We explain how augmentedAddition\((x, y)\) and augmentedMultiplication\((x, y)\) can be obtained from \( a_e \) and \( b_e \) in Sections III and IV, respectively, using a “recomposition” algorithm presented in Section II.

In the following, we need to use a definition inspired from Harrison’s definition [6] of function \( \text{ulp} \) (“unit in the last place”). If \( x \) is a floating-point number different from \(-\Omega\), first define \( \text{pred}(x) \) as the floating-point predecessor of \( x \), i.e., the largest floating-point number \(< x \). We define \( \text{ulp}_H(x) \) as follows.

**Definition 1** (Harrison’s \( ulp \)). If \( x \) is a floating-point number, then \( \text{ulp}_H(x) \) is

\[
|x| - \text{pred}(|x|) .
\]

Notation \( \text{ulp}_H \) is to avoid confusion with the usual definition of function \( \text{ulp} \). The usual \( \text{ulp} \) and function \( \text{ulp}_H \) differ at powers of 2, except in the subnormal domain. For instance, \( \text{ulp}(1) = 2^{-p+1} \), whereas \( \text{ulp}_H(1) = 2^{-p} \). One easily checks that if \(|t|\) is not a power of 2, then \( \text{ulp}(t) = \text{ulp}_H(t) \), and if \(|t| = 2^k\), then \( \text{ulp}(t) = 2^{k-p+1} = 2\text{ulp}_H(t) \), except in the subnormal range where \( \text{ulp}(t) = \text{ulp}_H(t) = 2^{2\min-p+1} \).

The reason for choosing function \( \text{ulp}_H \) instead of function \( \text{ulp} \) is twofold:

- if \( t > 0 \) is a real number, each time \( RN_0(t) \) differs from \( RN_e(t) \), \( RN_0(t) \) will be the floating-point predecessor of \( RN_e(t) \), because \( RN_0(t) \neq RN_e(t) \) implies that \( t \) is what we call a “halfway case” in Section II: it is exactly halfway between two consecutive floating-point numbers, and in that case, \( RN_0(t) \) is the one of these two FP numbers which is closest to zero and \( RN_e(t) \) is the other one. Hence, in these cases, to obtain \( RN_0(t) \) we will have to subtract from \( RN_e(t) \) a number which is exactly \( \text{ulp}_H(RN_e(t)) \) (for negative \( t \), for symmetry reasons, we will have to add \( \text{ulp}_H(RN_e(t)) \) to \( RN_e(t) \));

- there is a very simple algorithm for computing \( \text{ulp}_H(t) \) in the range where we need it (Algorithm 4 below).

Let us now briefly recall the classical Algorithms Fast2Sum, 2Sum, and Fast2Mult.

### ALGORITHM 1: Fast2Sum\((x, y)\). The Fast2Sum algorithm [4].

\[
a_e \leftarrow RN_e(x + y) \\
y' \leftarrow RN_e(a_e - x) \\
b_e \leftarrow RN_e(y - y')
\]

**Lemma 1.** If \( x = 0 \) or \( y = 0 \), or if the floating-point exponents \( e_x \) and \( e_y \) of \( x \) and \( y \) satisfy \( e_x \geq e_y \), then

1. the two variables \( a_e \) and \( b_e \) returned by Algorithm 1 (Fast2Sum) satisfy \( a_e + b_e = x + y \);
2. the operations performed at lines 2 and 3 of Algorithm 1 are exact operations: \( y' = a_e - x \) and \( b_e = y - y' \).

See for instance [13] for a proof. Hence, the variable \( b_e \) returned by Algorithm 1 is the error of the floating-point addition \( a_e = RN_e(x + y) \). The second property given in Lemma 1 will be useful in Section IV-C. In practice, condition “\( e_x \geq e_y \)” may be hard to check. However, if \(|x| \geq |y|\) then that condition is satisfied. Algorithm 1 is immune to spurious overflow: it was proved in [1] that if the addition \( RN_e(x + y) \) does not overflow then the other two operations cannot overflow.
Algorithm 2 (2Sum) gives the same results $a_e$ and $b_e$ as Algorithm 1, but without any requirement on the exponents of $x$ and $y$. It is almost immune to spurious overflow: if $|x| \neq \Omega$ and the addition $\text{RN}_e(x + y)$ does not overflow then the other five operations cannot overflow [1].

A similar algorithm, Algorithm 3 (Fast2Mult), makes it possible to express the exact product of two floating-point numbers $x$ and $y$ as the round of the product $\text{RN}_e(xy)$ and an error term. It requires the availability of an FMA (fused multiply-add) instruction. To be exactly representable as the sum of two floating-point numbers, the exact product must not be too tiny. Several sufficient conditions appear in the literature (such as the exponents $e_x$ and $e_y$ satisfying $e_x + e_y \geq e_{\min} + p - 1$, see [14] for a proof). We will use a slightly different condition, given by Lemma 2 below.

Algorithm 4 (Sterbenz Lemma). If $x$ and $y$ are floating-point numbers that satisfy $x/2 \leq y \leq 2x$, then $x - y$ is a floating-point number, which implies $\text{RN}_e(x - y) = x - y$.

Finally, we will sometimes use the following lemmas, whose proofs are straightforward.

Lemma 5. If $a$ is a nonzero floating-point number. If $t$ is a real number such that $|t| \leq |a|$ and $t$ is a multiple of $\text{ulp}(a)$, then $t$ is a floating-point number.

Lemma 6. If $t_1$ and $t_2$ are real numbers such that
1) $2^{e_{\min}} \leq |t_1|, |t_2| < \Omega + 2^{e_{\max}} - p$; 
2) there exists an integer $k$ such that $t_1 = 2^k \cdot t_2$; 
then $\text{RN}_e(t_1) = 2^k \cdot \text{RN}_e(t_2)$ and $\text{RN}_0(t_1) = 2^k \cdot \text{RN}_0(t_2)$.

As explained in Section II (where it corresponds to “Halfway Case 1”), when $\text{RN}_0(t)$ and $\text{RN}_e(t)$ differ, $\text{RN}_0(t)$ is obtained by subtracting $\text{sign}(t) \cdot \text{ulp}_H(\text{RN}_e(t))$ from $\text{RN}_e(t)$. Therefore, we need to be able to compute $\text{sign}(a) \cdot \text{ulp}_H(a)$.

Algorithm 4: MyulpH(a): Computes $\text{sign}(a) \cdot \text{pred}(|a|)$ and $\text{sign}(a) \cdot \text{ulp}_H(a)$ for $|a| > 2^{e_{\min}}$. Uses the FP constant $\psi = 1 - 2^{-p}$.

Lemma 7. The numbers $z$ and $\delta$ returned by Algorithm 4 satisfy:

- if $|a| > 2^{e_{\min}}$ then $z = \text{sign}(a) \cdot \text{pred}(|a|)$ and $\delta = \text{sign}(a) \cdot \text{ulp}_H(a)$;
- If $|a| \leq 2^{e_{\min}}$ then $z = a$ and $\delta = 0$.

Proof.
The fact that when $|a| > 2^{e_{\min}}$ the number $z$ returned by Algorithm 4 equals $\text{sign}(a) \cdot \text{pred}(|a|)$ is a direct consequence of [16, Lemma 3.6] (see also [9]). The value of $\delta$ immediately follows from that.

- If $|a| < 2^{e_{\min}}$ (i.e., $a$ is subnormal or zero), then $|2^{-p}a| < 2^{e_{\min}} - p = 2^{e_{\min}} - 2^{p-1}$, from which we obtain $|\psi - a| < 2^{p-1}$, thus $z = \text{RN}_H(\psi) = a$ and $\delta = 0$.
- Finally, if $|a| = 2^{e_{\min}}$, the tie-to-even rule implies $z = \text{RN}_H(\psi) = a$ and $\delta = 0$.

The fact that the radix is 2 is important here (a counterexample in radix 10 is $p = 3$ and $a = 101$). This means that our work cannot be straightforwardly generalized to decimal floating-point arithmetic.

II. RECOMPOSITION

In this section, we start from two FP numbers $a_e$ and $b_e$, that satisfy $a_e = \text{RN}_e(t)$, with $t = a_e + b_e$, and we assume $|a_e| > 2^{e_{\min}}$. These numbers may have been preliminarily generated by the 2Sum, Fast2Sum or Fast2Mult algorithms.
(Algorithms 1, 2, and 3). We want to obtain from $a_e$ and $b_e$ two
FP numbers $a_0$ and $b_0$ such that $a_0 = \text{RN}_0(t)$ and $a_0 + b_0 = t$.
Before giving the algorithm, let us present the basic principle
in the case $2^{-\infty} < t < \Omega$ (t is thus assumed positive to
simplify the presentation). If $t$ is not halfway between two
consecutive FP numbers, we know that $a_0 = a_e$ and $b_0 = b_e$.
If $t$ is halfway between two FP numbers (one of them being
$a_e$), then two cases may occur:

- **Halfway case 1:** $t = a_e - \frac{1}{2} \text{ulp}_H(a_e)$ (i.e., $b_e = -\frac{1}{2} \text{ulp}_H(a_e)$);
- **Halfway case 2:** $t = a_e + \frac{1}{2} \text{ulp}_H(a_e)$ (i.e., $b_e = +\frac{1}{2} \text{ulp}_H(a_e)$).

In the second case, $a_e$ is already equal to $t$ rounded to zero, so
we must choose $a_0 = a_e$ and $b_0 = b_e$. In the first case, $a_0$ is the
floating-point predecessor of $a_e$, and $b_0 = \frac{1}{2} \text{ulp}_H(a_e) = -b_e$.

Hence, to find $a_0$ and $b_0$ we must first detect if we are in
Halfway case 1: it is the only case where $(a_0, b_0)$ differs from
$(a_e, b_e)$. That detection is done using Algorithm 4 (MyulpH).

![Figure 2: Halfway case 1: $t = a_e - (1/2)\text{ulp}_H(a_e)$, where $t = a_e + b_e$. We have $a_0 = a_e - \text{ulp}_H(a_0)$ and $b_0 = -b_e$.](image)

**Algorithm 5:** Recomp($a_e, b_e$). From two FP
numbers $a_e$ and $b_e$ such that $a_e = \text{RN}_e(a_e + b_e)$
and $|a_e| > 2^{-\infty}$, computes $a_0$ and $b_0$ such that
$a_0 + b_0 = a_e + b_e$ and $a_0 = \text{RN}_0(a_e + b_e)$.

```plaintext
1) if $|z| = \pm \infty$ then return $(z, 0)$
2) if $\delta = 0$ then return $(a_0, b_0)$
3) if $\delta = \pm 1$ then return $(a_0, b_0)$
4) if $\delta = \pm 0$ then return $(a_0, b_0)$
```

augmentedMultiplication this will require a special handling
(see Sections IV-C and IV-D).

In the next two sections, we examine how Algorithm 5
can be used to compute augmentedAddition($x, y$) and
augmentedMultiplication($x, y$).

### III. USE OF ALGORITHM RECOMP FOR IMPLEMENTING
**AUGMENTED ADDITION**

From two input floating-point numbers $x$ and $y$, we wish to
calculate $\text{RN}_0(x + y)$ and $(x + y) - \text{RN}_0(x + y)$. We recall that
when $(x + y) - \text{RN}_0(x + y)$ equals zero, the IEEE 754-2019
Standard requires that it should be returned with the sign of
$\text{RN}_0(x + y)$. Let us first give a simple algorithm (Algorithm 6,
below) that returns a correct result (possibly with a wrong
sign for $b_0$ when it is zero) when no exception occurs (i.e., the
returned values are finite floating-point numbers).

**Algorithm 6:** AA-Simple($x, y$): computes
augmentedAddition($x, y$) when no exception occurs.

1. if $|x| > |y|$ then
2. swap($x, y$)
3. end if
4. $(a_e, b_e) \leftarrow \text{Fast2Sum}(x, y)$
5. $(a_0, b_0) \leftarrow \text{Recomp}(a_e, b_e)$
6. return $(a_0, b_0)$

**Theorem 1.** The values $a_0$ and $b_0$ returned by Algorithm 6
satisfy:

1) if $|x + y| < \Omega + 2^{e_{\max} - p} = (2 - 2^{-p})2^{e_{\max}}$ then
$(a_0, b_0)$ is equal to augmentedAddition($x, y$), with the possible
exception that if $b_0 = 0$ it may have a sign that differs
from the one specified in the IEEE 754-2019 Standard;
2) if $|x + y| = \Omega + 2^{e_{\max} - p}$ then $a_0 = \pm \infty$ and $b_0$ is
$\pm \infty$ (with a sign different from the one of $a_0$), whereas
the correct values would have been $a_0 = \pm \Omega$ and $b_0 =
\pm 2^{e_{\max} - p}$ (with the appropriate signs);
3) if $|x + y| > \Omega + 2^{e_{\max} - p}$ then $a_0 = \pm \infty$ (with the
appropriate sign) and $b_0$ is either NaN or $\pm \infty$ (possibly with
a wrong sign), whereas the standard requires $a_0 = b_0 = \infty
(with the same sign as $x + y$).

Note that if we are certain that $|x| \neq \Omega$ (so that $2\text{Sum}(x, y)$

- This is illustrated by Figures 2 and 3, and this leads to
  Algorithm 5 below. In Algorithm 5, when the number $-2 \cdot b_e$
is equal to $\delta$ (i.e., when Halfway case 1 occurs), we must
return $a_0 = a_e - \delta = \text{sign}(a_e) \cdot \text{pred}(|a_e|)$. This explains why
in that case the value of $a_0$ returned by the algorithm is $z$. We
obtain Lemma 8 below.

**Lemma 8.** If $2^{-\infty} < |a_e| \leq \Omega$ then the two floating-point
numbers $a_0$ and $b_0$ returned by Algorithm 5 satisfy

$$
\begin{align*}
a_0 &= \text{RN}_0(a_e + b_e), \\
a_0 + b_0 &= a_e + b_e.
\end{align*}
$$

Condition $2^{-\infty} < |a_e|$ in Lemma 8 is necessary: if
$|a_e| \leq 2^{-\infty}$, an immediate consequence of Lemma 7 is
that Algorithm 5 returns $a_0 = a_e$ and $b_0 = b_e$. This is
not a problem for implementing augmentedAddition thanks
to Lemma 3, as we are going to see in Section III. For
can be called without any risk of spurious overflow) we can replace lines 1 to 4 of the algorithm by a simple call to 2Sum\((x, y)\). Note also that Theorem 1 implies that each time \(a_0\) is a finite floating-point number, Algorithm 6 returns a correct result (with a possible wrong sign for \(b_0\) when it is zero).

The first item in Theorem 1 is an immediate consequence of the properties of the Fast2Sum and Recomp algorithms. Let us momentarily ignore the signs of zero variables. We have \(a_e = \text{RN}_e(x + y)\) and \(a_e + b_e = x + y\). Hence,

- if \(|a_e| > 2^{\text{emin}}\) then Recomp\((a_e, b_e)\) gives the expected result;
- if \(|a_e| \leq 2^{\text{emin}}\) then from Lemma 3, we know that the floating-point addition of \(x\) and \(y\) is exact, hence \(b_e = 0\).

We easily deduce that Recomp\((a_e, b_e)\) which is the expected result. In particular, if \(a_e = 0\) then we obtain \(a_0 = b_0 = 0\).

Now, let us reason about the signs of zero variables. Note that \(a_0 = 0\) is possible only when \(x + y = 0\). A quick look at Fast2Sum and MyulpH shows that when \(x + y = 0\), \(a_0 = 0\) with the same sign as \(a_e\), which corresponds to what is requested by IEEE 754-2019. Hence, when \(a_0 = 0\), it has the right sign.

When \(b_0 = 0\), this may come from two possible cases: either \(x + y\) is a nonzero floating-point number (in which case \(a_0 = 0\) is that number), or \(x + y = 0\). In both cases \(b_0\) should be zero with the same sign as \(a_e\). Tables I and II give the values of \(b_0\) returned by Algorithm 6 in these two cases. One can see that when \(b_0 = 0\), its sign is not always correct.

### TABLE I: Value of \(b_0\) computed by Algorithm 6 and value of \(b_0\) specified by the IEEE-754 Standard when \(x + y\) is a nonzero floating-point number (i.e., \(b_e = \pm 0\)).

<table>
<thead>
<tr>
<th>Case</th>
<th>computed (b_0)</th>
<th>correct (b_0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(y \neq 0) and (</td>
<td>a</td>
<td>&gt; 2^{\text{emin}})</td>
</tr>
<tr>
<td>(y \neq 0) and (</td>
<td>a</td>
<td>\leq 2^{\text{emin}})</td>
</tr>
<tr>
<td>(y = +0) and (</td>
<td>a</td>
<td>&gt; 2^{\text{emin}})</td>
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<td>a</td>
<td>\leq 2^{\text{emin}})</td>
</tr>
<tr>
<td>(y = -0) and (</td>
<td>x</td>
<td>&gt; 2^{\text{emin}})</td>
</tr>
<tr>
<td>(y = -0) and (</td>
<td>x</td>
<td>\leq 2^{\text{emin}})</td>
</tr>
</tbody>
</table>

### TABLE II: Value of \(b_0\) computed by Algorithm 6 and value of \(b_0\) specified by the IEEE-754 Standard when \(x + y = 0\).

<table>
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<th>Case</th>
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<th>correct (b_0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(x = -y) and (x \neq 0)</td>
<td>-0</td>
<td>+0</td>
</tr>
<tr>
<td>(x = +y) and (y = +0)</td>
<td>0</td>
<td>+0</td>
</tr>
<tr>
<td>(x = +y) and (y = -0)</td>
<td>+0</td>
<td>+0</td>
</tr>
<tr>
<td>(x = -y) and (y = +0)</td>
<td>0</td>
<td>+0</td>
</tr>
<tr>
<td>(x = -y) and (y = -0)</td>
<td>+0</td>
<td>+0</td>
</tr>
</tbody>
</table>

However, if the signs of the zero variables matter in the target application, there is a simple solution. Since the sign of \(a_0\) is always correct, and since when \(b_0 = 0\) it must be returned with the sign of \(a_0\), it suffices to add to add the following lines to Algorithm 6 after Line 5:

```
if \(b_0 = 0\) then
    \(b_0 \leftarrow (0+) \times a_0\)
end if
```

Alternatively, one can also use the `copySign` instruction specified by the IEEE 754 Standard [8] if it is faster than a floating-point multiplication on the system being used: `copySign(x, y)` has the absolute value of \(x\) and the sign of \(y\).

The second item in Theorem 1 follows immediately by applying Algorithm 6 to the corresponding input value.

Concerning the third item in Theorem 1, Table III gives the values returned by Algorithm 6 when \(|x + y| > \Omega + 2^{\text{emin}}\) and compares them with the correct values.

### TABLE III: Values obtained using Algorithm 6 (possibly with a replacement of Fast2Sum by 2Sum) when \(|x + y| > 2^{\text{emin}}(2 - 2^{-p})\).

<table>
<thead>
<tr>
<th>Case</th>
<th>Variant of Algorithm 6 with ((a_e, b_e)) obtained through Fast2Sum</th>
<th>Result required by the standard</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_0)</td>
<td>+(\infty) (\times \text{sign}(x + y))</td>
<td>+(\infty) (\times \text{sign}(x + y))</td>
</tr>
<tr>
<td>(b_0)</td>
<td>NaN</td>
<td>+(\infty) (\times \text{sign}(x + y))</td>
</tr>
</tbody>
</table>

If the considered applications only require augmentedAddition to follow the specifications when no exception occurs, Algorithm 6 (possibly with the above given additional lines if the signs of zeroes matter) is a good candidate. If we wish to always follow the specifications, we suggest using Algorithm 7 below.

### ALGORITHM 7: AA-Full\((x, y)\): computes augmentedAddition\((x, y)\) in all cases.

```
1: if \(|y| > |x|\) then
2:    swap\((x, y)\)
3: end if
4: \((a_e', b_e') \leftarrow \text{Fast2Sum}(x, y)\)
5: \((a_0, b_0) \leftarrow \text{Recomp}(a_e, b_e)\)
6: if \(b_0 = 0\) then
7:    \(b_0 \leftarrow (0+) \times a_0\)
8: else if \(|a_e| = +\infty\) then
9:    \((a_e', b_e') \leftarrow \text{Fast2Sum}(0.5x, 0.5y)\)
10: if \(a_e' = 2^{\text{emin}}\) and \(b_e' = -2^{\text{emin}}\) then
11:    \(a_0 \leftarrow \text{RN}_e(a_e' \times (2 - 2^{-p+1})\)
12:    \(b_0 \leftarrow -2b_e'\)
13: else
14:    \(a_0 \leftarrow a_e'\) (infinity with right sign)
15:    \(b_0 \leftarrow a_e'\)
16: end if
17: end if
18: return \((a_0, b_0)\)
```

**Theorem 2.** The output \((a_0, b_0)\) of Algorithm 7 is equal to augmentedAddition\((x, y)\).

**Proof.**

1) if \(|x + y| < \Omega + 2^{\text{emin}}\) then Item 1 of Theorem 1 tells us that the values \(a_0\) and \(b_0\) computed at Line 5 of Algorithm 7 are equal to augmentedAddition\((x, y)\), with the possible exception that if \(b_0 = 0\) it may have a sign that differs from the one specified in the IEEE 754-2019...
Standard. This possible error in the sign of $b_0$ is corrected at Lines 6-7.

2) if $|x + y| = \Omega + 2^{\epsilon_{\text{max}} - p}$ then $|a_e| = +\infty$. In that case, since $\frac{1}{2} \cdot |x + y| = \frac{\Omega}{2} + 2^{\epsilon_{\text{max}} - p - 1} = 2^{\epsilon_{\text{max}}} - 2^{\epsilon_{\text{max}} - p - 1}$, at Line 9 we obtain

$$a' = \text{sign}(x + y) \cdot 2^{\epsilon_{\text{max}}}$$

and

$$b' = -\text{sign}(x + y) \cdot 2^{\epsilon_{\text{max}} - p - 1}.$$  

In that case, Lines 10-12 of the algorithm return the correct values

$$a_0 = \text{sign}(x + y) \cdot \Omega$$

and

$$b_0 = \text{sign}(x + y) \cdot 2^{\epsilon_{\text{max}} - p - 1}.$$  

3) if $|x + y| > \Omega + 2^{\epsilon_{\text{max}} - p}$ then $|a_e| = +\infty$, and the sum $(x + y)/2$ computed using Fast2Sum at Line 9 (without overflow since $|x + y|/2$ is less than or equal to the maximum of $|x|$ and $|y|$) will be or absolute value (strictly) larger than $2^{\epsilon_{\text{max}}} - 2^{\epsilon_{\text{max}} - p - 1}$, hence Lines 14-15 of the algorithm will be executed, and we will obtain $a_0 = b_0 = \text{sign}(x + y) \cdot \infty$, as expected.

IV. USE OF ALGORITHM RECOMP FOR IMPLEMENTING AUGMENTEDMULTIPLICATION

A. General case

From two input floating-point numbers $x$ and $y$, we wish to compute $\text{RN}_0(x \cdot y)$ and $x \cdot y - \text{RN}_0(x \cdot y)$ (or, merely, $\text{RN}_0(x \cdot y - \text{RN}_0(x \cdot y))$) when $x \cdot y \neq \text{RN}_0(x \cdot y)$ is not a floating-point number). As we did for augmentedAddition, let us first present a simple algorithm (Algorithm 8 below). Unfortunately, it will be less general than the simple addition algorithm: this is due to the fact that when the absolute value of the product of two floating-point numbers is less than or equal to $2^{\epsilon_{\text{min}} + p}$, it may not be exactly representable by the sum of two floating-point numbers (an example is $x = 1 + 2^{-p+1}$ and $y = 2^{\epsilon_{\text{min}}} + 2^{\epsilon_{\text{min}} - p - 1}$; their product $2^{\epsilon_{\text{min}} + 2^{\epsilon_{\text{min}} - p + 2}} + 2^{\epsilon_{\text{min}} - 2p + 2}$ cannot be a sum of two FP numbers, since such a sum is necessarily a multiple of $2^{\epsilon_{\text{min}} - p + 1}$).

**ALGORITHM 8: AM-Simple$(x, y)$: computes augmentedMultiplication$(x, y)$ when $2^{\epsilon_{\text{min}} + p} + 2^{\epsilon_{\text{min}}} < |x \cdot y| < \Omega + 2^{\epsilon_{\text{max}} - p}$.

1: $(a_e, b_e) \leftarrow \text{Fast2Mult}(x, y)$
2: $(a_0, b_0) \leftarrow \text{Recomp}(a_e, b_e)$
3: return $(a_0, b_0)$

**Theorem 3.** The values $a_0$ and $b_0$ returned by Algorithm 8 satisfy:

1) If $2^{\epsilon_{\text{min}} + p} + 2^{\epsilon_{\text{min}}} < |x \cdot y| < \Omega + 2^{\epsilon_{\text{max}} - p}$ (which implies $2^{\epsilon_{\text{min}} + p} + 2^{\epsilon_{\text{min}} + 1} \leq |\text{RN}_e(x \cdot y)| \leq \Omega$) then $(a_0, b_0)$ is equal to augmentedMultiplication$(x, y)$, with the possible exception that if $b_0 = 0$ it may have a sign that differs from the one specified in the IEEE 754-2019 Standard;

2) if $|x \cdot y| = \Omega + 2^{\epsilon_{\text{max}} - p} = (2 - 2^{-p}) \cdot 2^{\epsilon_{\text{max}}}$ then

$$a_0 = +\infty \text{ (with the sign of } x \cdot y) \text{ and } b_0 = +\infty \text{ (with the opposite sign)} \text{ whereas the correct values would have been } a_0 = \pm \Omega \text{ and } b_0 = \pm 2^{\epsilon_{\text{max}} - p} \text{ (both with the sign of } x \cdot y);$$

3) if $|x \cdot y| > \Omega + 2^{\epsilon_{\text{max}} - p}$, then $a_0 = +\infty$ (with the sign of $x \cdot y$) and $b_0 = +\infty$ (with the opposite sign) whereas the correct values would have been $a_0 = b_0 = +\infty$ (with the sign of $x \cdot y$).

**Proof.** The first item in Theorem 3 is a consequence of Lemma 2 and Lemma 8. If

$$2^{\epsilon_{\text{min}} + p} + 2^{\epsilon_{\text{min}}} < |x \cdot y| < \Omega + 2^{\epsilon_{\text{max}} - p}$$

then $2^{\epsilon_{\text{min}} + p} + 2^{\epsilon_{\text{min}} + 1} \leq |RN_e(x \cdot y)| \leq \Omega$, therefore

- $(a_e, b_e) = \text{Fast2Mult}(x, y)$ gives $a_e + b_e = x \cdot y$;
- $|a_e| > 2^{\epsilon_{\text{min}}}$;

therefore $	ext{Recomp}(a_e, b_e)$ returns the expected result.

The second item in Theorem 3 follows immediately by applying Algorithm 8 to the corresponding input value. Concerning the third item in Theorem 3, Table IV gives the values returned by Algorithm 8 when $|x \cdot y| > \Omega + 2^{\epsilon_{\text{max}} - p}$.

**TABLE IV: Values obtained using Algorithm 8 when $|x \cdot y| > 2^{\epsilon_{\text{max}} - 2^{-p}}$.

<table>
<thead>
<tr>
<th>Algorithm 8</th>
<th>Result required by the standard</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_0$</td>
<td>$+\infty \cdot \text{sign}(x \cdot y)$</td>
</tr>
<tr>
<td>$b_0$</td>
<td>$-\infty \cdot \text{sign}(x \cdot y)$</td>
</tr>
</tbody>
</table>

As with the addition algorithm, if the signs of the zero variables matter in the target application and if Condition 1 of Theorem 3 is satisfied, it suffices to add the following lines to Algorithm 8 after Line 2:

```plaintext
if $b_0 = 0$ then
    $b_0 \leftarrow (+0) \times a_0$
end if
```

(and, again, function $	ext{copySign}$ can be used if it is faster than a floating-point multiplication). Another solution is to notice that in Case 1 of Theorem 3, $x \cdot y - a_0$ is a floating-point number, therefore one can just compute $a_0$ with Algorithm 8 and obtain $b_0$ with one FMA instruction, as $\text{RN}_e(x \cdot y - a_0)$. As we are going to see that solution is useful even when Condition 1 of Theorem 3 is not satisfied.

Let us now build another augmented multiplication algorithm, Algorithm 9 below, that returns a correct result even if the condition of Case 1 of Theorem 3 (i.e., $2^{\epsilon_{\text{min}} + p} + 2^{\epsilon_{\text{min}}} < |x \cdot y| < \Omega + 2^{\epsilon_{\text{max}} - p}$) is not satisfied. We need to be able to address the cases $\text{RN}_e(x \cdot y) = \pm \infty$ (that correspond to items 2 and 3 in Theorem 3) and $|\text{RN}_e(x \cdot y)| \leq 2^{\epsilon_{\text{min}} + p}$.
This will be done by scaling the calculation, i.e., by finding a suitable power of 2, say $2^k$, such that $2^k x$ is computed without over/underflow, and the requested calculations (in particular those in Algorithm 8) can be done safely with inputs $x' = 2^k x$ and $y$. We need to consider three cases:

- when $\text{RN}_e(x \cdot y) = \pm \infty$, we choose $2^k = 1/2$. This case is dealt with in Section IV-B;
- when $|\text{RN}_e(x \cdot y)| \leq 2^{e_{\min}+1} - 2^{e_{\min}-p-1}$, we choose $2^k = 2^p$. This case is dealt with in Section IV-C;
- when $2^{e_{\min}+1} \leq |\text{RN}_e(x \cdot y)| \leq 2^{e_{\min}+p}$, we choose $2^k = 2^p$. This case is dealt with in Section IV-D.

Note that when $|\text{RN}_e(x \cdot y)| \leq 2^{e_{\min}+p}$ (i.e., in the last two cases mentioned just above), $\text{RN}_0(x \cdot y - \text{RN}_0(x \cdot y)) = 0$ does not mean that $x \cdot y - \text{RN}_0(x \cdot y) = 0$. This slightly complicates the choice of the sign of $b_0$ when it is equal to zero. More precisely, when $b_0 = 0$, the sign of $b_0$ must be:

- the sign of $a_0$ (i.e., the sign of $xy$) when $xy - a_0 = 0$;
- the real sign of $xy - a_0$ otherwise.

Fortunately, in both cases, this is the same sign as the one of $\text{RN}_e(x \cdot y - a_0)$, which is obtained using an FMA instruction. Hence, when $b_0 = 0$, one can return $(+0) \cdot \text{RN}_e(x \cdot y - a_0)$ (the multiplication by $(+0)$ is necessary to handle the case $xy - a_0 = 2^{e_{\min}-p}$, for which functions $\text{RN}_0$ and $\text{RN}_e$ differ).

### B. First special case: if $\text{RN}_e(x \cdot y) = \pm \infty$

In this case, which corresponds to Lines 2–11 in Algorithm 9, we need to know if we are in Case 2 (i.e., $|x \cdot y| = \Omega + 2^{e_{\max}-p}$) or Case 3 (i.e., $|x \cdot y| > \Omega + 2^{e_{\max}-p}$) of Theorem 3. Hence our problem reduces to checking if $|x \cdot y| = \Omega + 2^{e_{\max}-p}$. That problem is addressed easily. It suffices to compute $(a'_e, b'_e) = \text{Fast2Mult}(0.5 \cdot x, y)$:

- If $|x \cdot y| = \Omega + 2^{e_{\max}-p}$, then $(x/2) \cdot y$ is computed by Fast2Mult without overflow, which allows one to check its equality with $(\Omega + 2^{e_{\max}-p}) / 2$;
- If it turns out that $|x \cdot y/2| \neq (\Omega + 2^{e_{\max}-p}) / 2$ it suffices to return $a_0 = b_0 = \text{RN}_e(x \cdot y)$: they will be infinities with the right sign.

### C. Second special case: if $|\text{RN}_e(x \cdot y)| \leq 2^{e_{\min}+1} - 2^{e_{\min}-p+1}$

In that case,

$$|x \cdot y - \text{RN}_0(x \cdot y)| \leq 2^{e_{\min}-p},$$

and thus $\text{RN}_0(x \cdot y - \text{RN}_0(x \cdot y)) = 0$, so we have to return $b_0 = 0$ (with the sign of $\text{RN}_e(x \cdot y - a_0)$), and we only have to focus on the computation of $a_0 = \text{RN}_0(x \cdot y)$. We also assume that $\text{RN}_e(x \cdot y) \neq 0$ (otherwise, it suffices to return the pair $(0, 0)$, with the sign of $xy$). We therefore have

$$2^{e_{\min}-p} < |x \cdot y| < 2^{e_{\min}+1} - 2^{e_{\min}-p}.$$  

Note that (6) implies

$$2^{e_{\min}+p} < |2^p x \cdot y| < 2^{e_{\min}+p+1} - 2^{e_{\min}+p}.$$  

Let us first give the general reasoning behind the calculations of Lines 16–25 of Algorithm 9 (detailed proof will follow). Let $a_e$ be $\text{RN}_e(x \cdot y)$. Since the distance between consecutive floating-point numbers in the vicinity of $x y$ is $2^{e_{\min}-p+1}$ (we are in the subnormal range), we have the following property:

- if $xy = a_e - 2^{e_{\min}-p}$ (i.e., we are in what we call “Halfway case I” in Section II), then
  $$a_0 = a_e - 2^{e_{\min}-p+1};$$
- otherwise, $a_0 = a_e$.

Therefore, we need to compare $xy$ with $a_e - 2^{e_{\min}-p}$. This cannot be done straightforwardly, because $xy$ is not necessarily representable exactly as the sum of two FP numbers (Lemma 2 does not hold). Instead, we will compare $2^p xy$ with $2^{2p} a_e - 2^{e_{\min}+p}$. The first step for doing that will be to express $2^p xy$ as the sum of two FP numbers $t_1$ and $t_2$ using Algorithm Fast2Mult. Then, to compare $t_1 + t_2$ with $2^{2p} a_e - 2^{e_{\min}+p}$, we will first show that the subtraction $t_3 = t_1 - 2^{2p} a_e$ is performed exactly, so that it will suffice to compare $t_2 + t_3$ with $-2^{e_{\min}+p}$.

So, we successively compute (using FMA instructions)

$$t_1 = \text{RN}_e((2^p x \cdot y), y)$$
$$t_2 = \text{RN}_e((2^p x \cdot y) - t_1) = x \cdot y \cdot 2^{2p} - t_1$$
$$t_3 = \text{RN}_e(t_1 - a_e \cdot 2^p).$$

First, $t_1$ can be computed without overflow:

- $|x \cdot y| < 2^{e_{\min}+1}$ and, since $x \cdot y \neq 0$, $|y| \geq 2^{e_{\min}-p+1}$.
- Therefore, $|x| \cdot 2^p < 2^{e_{\min}+1}$. Using (4), this implies that $|x \cdot 2^p| < 2^{e_{\max}+1}$, hence $x \cdot 2^p$ is a floating-point number;
- now, $|(2^p x \cdot y)| < 2^{e_{\min}+1}+2^p < 2^{e_{\min}+p} < 2^{e_{\max}+1}$ since $e_{\min} < 0$.

Therefore, $|2^p x \cdot y|$ is below the overflow threshold, and

$$|t_1 - 2^{2p} xy| \leq \frac{1}{2} \text{ulp}(t_1). \tag{8}$$

The fact that $t_2 = x \cdot y \cdot 2^{2p} - t_1$ comes from Lemma 2 and (7).

Let us show that $\theta_3 = t_1 - a_e \cdot 2^p$ is a floating-point number. This will imply

$$t_3 = \theta_3 = t_1 - a_e \cdot 2^p$$

(hence, $\theta_3$ can be computed with an FMA, or with an exact multiplication by $2^p$ followed by a subtraction). From (7) we obtain

$$2^{e_{\min}+p} \leq |t_1| \leq 2^{e_{\min}+2p+1} - 2^{e_{\min}+p+1}$$

and $\text{ulp}(t_1) \leq 2^{e_{\min}+p+1}$.

Since $a_e$ (as any FP number) is a multiple of $2^{e_{\min}-p+1}$, the number $2^{2p} \cdot a_e$ is a multiple of $2^{e_{\min}+p+1}$. Therefore, $\theta_3$ is a multiple of ulp($t_1$).

Now, (5) gives $x \cdot y \cdot 2^{e_{\min}-p} \leq a_e \leq x \cdot y + 2^{e_{\min}-p}$, from which we deduce

$$x \cdot y \cdot 2^{2p} - 2^{e_{\min}+p} \leq a_e \cdot 2^p \leq x \cdot y \cdot 2^{2p} + 2^{e_{\min}+p},$$

which implies, using (8),

$$t_1 - \frac{1}{2} \text{ulp}(t_1) - 2^{e_{\min}+p} \leq a_e \cdot 2^p \leq t_1 + \frac{1}{2} \text{ulp}(t_1) + 2^{e_{\min}+p},$$

$$t_1 - \frac{1}{2} \text{ulp}(t_1) - 2^{e_{\min}+p} \leq a_e \cdot 2^p \leq t_1 + \frac{1}{2} \text{ulp}(t_1) + 2^{e_{\min}+p},$$
ALGORITHM 9: AM-Full(x, y): computes augmentedMultiplication(x, y) in all cases.

1. $a_e \leftarrow \text{RN}_e(x \cdot y)$
2. if $|a_e| = +\infty$ then
3. $x' \leftarrow 0.5 \cdot x$
4. $(a', b') \leftarrow \text{Fast2Mult}(x', y)$
5. if $(a' = 2^{\max} \text{ and } b' = -2^{\max+1}) \text{ or } (a' = -2^{\max} \text{ and } b' = +2^{\max+1})$ then
6. $a_0 \leftarrow \text{RN}_e(a' \cdot (2 - 2^{p+1}))$
7. $b_0 \leftarrow -2b'_e$
8. else
9. $a_0 \leftarrow a_e$ (infinity with right sign)
10. $b_0 \leftarrow a_e$
11. end if
12. else if $|a_e| \leq 2^{e_{\text{min}}+p}$ then
13. if $a_e = 0$ then
14. $a_0 \leftarrow a_e$
15. $b_0 \leftarrow a_e$
16. else if $|a_e| \leq 2^{e_{\text{min}}+1} - 2^{e_{\text{min}}+p}$ then
17. $b_0 \leftarrow 0$
18. $(t_1, t_2) \leftarrow \text{Fast2Mult}(x \cdot 2^p, y)$
19. $t_3 \leftarrow \text{RN}_e(t_1 - a_e \cdot 2^p)$
20. $z \leftarrow \text{RN}_e(t_3 + t_3)$
21. if $(z = \text{sign}(a_e) \cdot 2^{e_{\text{min}}+p})$ and $(\text{RN}_e(z - t_3) = t_2)$ then
22. $a_0 \leftarrow a_e - \text{sign}(a_e) \cdot 2^{e_{\text{min}}-p+1}$
23. else
24. $a_0 \leftarrow a_e$
25. end if
26. else
27. $(a', b') \leftarrow \text{AM-Simple}(2^px, y)$
28. $a_0 \leftarrow \text{RN}_e(2^{-p} \cdot a')$
29. $b_0 \leftarrow \text{RN}_e(2^{-p} \cdot b')$
30. if $\text{RN}_e(2^pb - b') = \text{sign}(b) \cdot 2^{e_{\text{min}}}$ then
31. $b_0 \leftarrow b - \text{sign}(b) \cdot 2^{e_{\text{min}}-p+1}$
32. else
33. $b_0 \leftarrow b$
34. end if
35. end if
36. else
37. $b_e \leftarrow \text{RN}_e(x \cdot y - a_e)$
38. $(a_0, b_0) \leftarrow \text{Recomp}(a_e, b_e)$
39. end if
40. if $b_0 = 0$ then
41. $b_0 \leftarrow (+0) \cdot \text{RN}_e(xy - a_0)$
42. end if
43. return $(a_0, b_0)$

Now, we can compute $a_0 = \text{RN}_0(x \cdot y)$. If $x \cdot y = a_e - \text{sign}(a_e) \cdot 2^{e_{\text{min}}-p}$ then $a_0 = a_e - \text{sign}(a_e) \cdot 2^{e_{\text{min}}+p+1}$ (computed without error), otherwise $a_0 = a_e$. Hence we have to decide whether $x \cdot y = a_e - \text{sign}(a_e) \cdot 2^{e_{\text{min}}-p}$. This is equivalent to checking if $t_2 + t_3 = -\text{sign}(a_e) \cdot 2^{e_{\text{min}}+p}$. This can be done as follows: first note that since $t_3$ is a multiple of ulp(t_1) and $|t_2| \leq \frac{1}{2} \text{ulp}(t_1)$, either $t_3 = 0$ or $|t_3| > |t_2|$. Therefore, Lemma 1 can be applied to the addition of $t_2$ and $t_3$. Item 2 of that lemma tells us if we define $z = \text{RN}_e(t_2 + t_3)$, then $\text{RN}_e(z - t_3) = z - t_3$. Therefore, checking if $t_2 + t_3 = -\text{sign}(a_e) \cdot 2^{e_{\text{min}}+p}$ is equivalent to checking if

$$z = -\text{sign}(a_e) \cdot 2^{e_{\text{min}}+p}$$

and

$$\text{RN}_e(z - t_3) = t_2.$$

D. Last special case: if $2^{e_{\text{min}}+1} \leq |\text{RN}_e(x \cdot y)| \leq 2^{e_{\text{min}}+p}$

That case corresponds to Lines 26–34 of Algorithm 9. In that case, we know that $x \cdot y - \text{RN}_0(x \cdot y)$ is of magnitude less than or equal to $2^{e_{\text{min}}}$, but is not necessarily a floating-point number. The standard requires that we return $a_0 = \text{RN}_0(x \cdot y)$ and $b_0 = \text{RN}_0(x \cdot y - \text{RN}_0(x \cdot y))$.

We start by applying Algorithm 8 to the product $(2^px) \cdot y$. That product can be computed without overflow:

- first, $|\text{RN}_e(x \cdot y)| \leq 2^{e_{\text{min}}+p}$ implies $|xy| \leq 2^{e_{\text{min}}+p + 2^{e_{\text{min}}}}$.

Also, $2^{e_{\text{min}}+1} \leq |\text{RN}_e(x \cdot y)|$ implies $y \neq 0$, therefore $|y| \leq 2^{e_{\text{min}}+p-1}$. Thus

$$|x| = \frac{|xy|}{|y|} \leq \frac{2^{e_{\text{min}}+p + 2^{e_{\text{min}}}}}{2^{e_{\text{min}}+p-1}} = 2^{2p+1} + 2^{p-1}.$$ Therefore $|2^px| \leq 2^{3p-1} + 2^{p-1} < 2^{e_{\text{max}}}$ using (4). Thus $(2^px)$ is below the overflow threshold.

- finally, $|xy| \leq 2^{e_{\text{min}}+p + 2^{e_{\text{min}}}}$ implies

$$|(2^px) \cdot y| \leq 2^{e_{\text{min}}+2p} + 2^{e_{\text{min}}+p},$$

which is less than $2^{e_{\text{max}}}$ from (4) and the fact that $e_{\text{min}}$ is negative.

Algorithm 8 applied to $(2^px) \cdot y$ returns two values, say $a'$ and $b'$, such that $a' = \text{RN}_0(2^px \cdot y)$ and $b' = 2^px \cdot y - a'$. We immediately deduce using Lemma 6 that $2^{-p}a'$ is the expected $\text{RN}_0(x \cdot y)$. Obtaining $\text{RN}_0(x \cdot y - 2^{-p}a') = \text{RN}_0(2^{-p}b')$ is slightly more tricky (Lemma 6 cannot be used because $|2^{-p}b'|$ can be strictly less than $2^{e_{\text{min}}}$). We first compute $\beta = \text{RN}_e(2^{-p}b')$. The number $\beta$ is equal to the expected $\text{RN}_0(2^{-p}b')$ unless we are in Halfway Case 1 of Section II, i.e., unless

$$\beta - (2^{-p}b') = \text{sign}(\beta) \cdot 2^{e_{\text{min}}-p} \quad (9)$$

in which case, one should replace $\beta$ by $\beta - \text{sign}(\beta) \cdot 2^{e_{\text{min}}-p+1}$. Equation (9) is equivalent to

$$2^p \beta - b' = \text{sign}(\beta) \cdot 2^{e_{\text{min}}},$$
a condition which is easy to test since the subtraction is exact: 
$2^p \beta - b'$ is a multiple of $2^{e_{\text{min}}-p+1}$, of magnitude less than or equal to $2^{e_{\text{min}}}$, hence it is a floating-point number.

All this gives Algorithm 9 and Theorem 4.

**Theorem 4.** The output $(a_0, b_0)$ of Algorithm 9 is equal to augmentedMultiplication$(x, y)$.

V. Formal proof

Arithmetic algorithms can be used in critical applications. The proof presented here is complex, with many particular cases to be considered. We have used the Coq proof assistant and the Flocq library [2] for our development towards Theorems 1 and 4.

Our formal proof is available as electronic appendix.

Note that we have aimed at genericity. In particular, we have tried to generalize the tie-breaking rule when possible. The precision and minimal exponent are hardly constrained as we only require $p > 1$ and $e_{\text{min}} < 0$. As explained above, the radix must be 2 as Algorithm 4 does not hold for radix 10 (the definitions and first properties of ulp$_H$ and RN$_0$ are generic enough).

The formal proof quite follows the mathematical proof described above. Of course, we had to add several lemmas and to define RN$_0$ and its properties. This definition was very similar to the definition of rounding-to-nearest with tie-breaking away from zero defined by the standard for decimal arithmetic [8], and most of the proofs were nearly identical.

We then proved the correctness of Algorithm 4. In this case for $|a| > 2^{e_{\text{min}}}$, the two RN$_c$ roundings may be replaced by a rounding to nearest with any tie-breaking rule (they may even differ). Algorithm 5 is also proven. Similarly, the two RN$_e$ roundings may in fact use any tie-breaking rule. The proof of Theorem 1 is then easily deduced, with Recomp using any two tie-breaking rules.

As on paper, the proof of Theorem 4 is more intricate, with many subcases, even if we handle only cases A (without the zeroes), C, and D. Here, the case split depends on the tie-breaking rule: the equalities may be either strict or large depending upon the tie-breaking rule. For the sake of simplicity, we chose to stick to the pen-and-paper proof and share the same case split. We then require some roundings to use tie-breaking to even. We were not able to generalize the proof at a reasonable cost to handle all tie-breaking rules. Nevertheless, the proof was formally done and we were able to prove the correctness of Theorems 1 and 4 (without considering overflows and signs of zeroes). The Coq statements are as follows (with few simplifications for the sake of readability). Note that c1...c7 are arbitrary tie-breaking rules.

**Definition** Recomp := fun c1 c2 a b =>
let z := round_flt c1 (psiax a) in
let d := round_flt c2 (z-b) in
if (Req_bool (2*b)) then (z-b) else (a,b).

**Definition** AA_Simple :: fun c1 c2 x y =>
let (x',y') := if (Rlt_bool (Rabs (Rabs x)) (Rabs y))
then (x,y) else (x,y) in
let (ae,be) := FastSum x' y' in
Recomp c1 c2 ae be.

**Definition** AM_Full :: fun c1 c2 c3 c4 c5 c6 c7 x y =>
lse ae := round_flt ZnearestE (x*y) in
if (Rle_bool (Rabs ae) (bpow (emin+prec))) then
(+ zero +)
if (Req_bool ae 0) then (0,0) else
(+ very small +)
if (Rle_bool (Rabs ae) (bpow (emin+1)) − bpow (emin-prec+1)) then
let t1 := round_flt c1 (x*y+bpow (2*prec)) in
let t2 := round_flt c2 (x*y+bpow (2*prec) − t1) in
let t3 := round_flt c3 (t1−ae+bpow (2*prec)) in
let z := round_flt ZnearestE (t2+t3) in
if (andb (Req_bool z (−sign(ae)*bpow (emin+prec)))
(Req_bool (round_flt (ZnearestE (z−t3)) t2))
then (ae−sign(ae)*bpow (emin+prec),0)
else (a,0).
Theorem 4.

A very important limitation of these proofs is that overflows, infinite numbers, and the signs of zeroes are not considered. We relied on the Flocq formalization that considers floating-point numbers as a subset of real numbers. Therefore, zeroes are merged and there are neither infinities, nor NaNs. It allows us to state the final theorems in the most understandable way: $a_0 = \text{RN}_0(t)$ and $a_0 + b_0 = t$ or at least $b_0 = \text{RN}_0(t − a_0)$ (with $t$ being either the sum or product of two floating-point numbers).

We have tried to develop additional formal proofs taken all exceptional behaviors into account (especially NaNs and overflows). We have relied on a modified version of the Binary definitions of Flocq and we have defined the full algorithms, with comparisons on FP numbers and possible overflows. It made both the algorithms and their specifications more complicated and less readable. Moreover, the comprehensive formal proofs were out of reach, both by lack of support lemmas and by combinatorial explosion of the subcases for each and every operation (NaN, overflow, signed zero, and so
This really calls for automations in Coq for handling FP numbers with exceptional behaviors, that is out of scope of this paper.

VI. IMPLEMENTATION AND COMPARISON

We have implemented the algorithms presented in this paper in binary64 (a.k.a. double precision) arithmetic, as well as emulation algorithms based on integer arithmetic, described below. We used an Intel Core i7-7500U x86_64 processor clocked at 2.7GHz under GNU/Linux (Debian 4.19.0-8-amd64), and the programs were compiled using GCC (Debian 8.3.0-6) 8.3.0, with the option -O3 -march=native. Our implementation, together with all testing and performance evaluation code, is available as additional material coming with this article; it can be downloaded at https://gitlab.com/ecuirrin/ieee754-2019-augmented-operations-reference-implementation and is archived at https://hal.archives-ouvertes.fr/hal-02137968.

Having an integer-based version of the augmented operations was important for comparison purposes, since there are no other implementations of these operations at the time we are going to see, the emulation code is on average on the number of cycles is measured as follows: the function 5c for the integer-based emulation of augmentedAddition algorithms, in Figures 4c for the integer-based emulation of augmentedAddition; and 5b for Algorithm 9 (AM-Full), and 4c for Algorithm 7 (AA-Full), respectively. For the augmentedAddition algorithms, in Figures 4a for Algorithm 6 (AA-Simple), 4b for Algorithm 7 (AA-Full), and 4c for the integer-based emulation of augmentedAddition;

5) The intermediate result \((-1)^{s_x} 2^{E_x} M \) is rounded to the nearest IEEE754 binary64 value \(a\), applying round-to-nearest-ties-to-zero rules. This rounding step is implemented as a “rounding to odd” [3] (with sticky bit) to \((-1)^{s_x} 2^{E_x} M'\), where \(M'\) is a 64-bit integer significand, followed by the actual rounding to the binary64 format. This code sequence is quite complicated as it must cope with a multitude of possible cases, such as overflow, gradual or complete underflow as well as exact zeroes. A trace of overflow, underflow and inexact rounding is kept during this rounding step.

6) The high-order word \(a\) is decomposed again into \((-1)^{s_x} 2^{E_x} M\). If it is finite, this value is subtracted from the intermediate result \((-1)^{s_x} 2^{E_x} M\), which, after appropriate leading-zero count and normalization shift, yields to \((-1)^{s_x} 2^{E_x} M_t\), where \(M_t\) is an integer significand stored on a 64-bit integer. This value \((-1)^{s_x} 2^{E_x} M_t\) is given to the same rounding code as the one used above, which yields \(b\) with round-to-nearest-ties-to-zero and a trace of overflow, underflow and inexact rounding.

7) Out of both traces for overflow, underflow and inexact a global IEEE754 flag setting is computed and applied to IEEE754 flag registers by executing a dummy FP operation that make the appropriate flags be raised.

The emulation code has the advantage of being the only version of our algorithms that is able to set the IEEE754 flags correctly and to be insensible to the prevailing IEEE754 rounding direction attribute. The FP-based algorithms may set the inexact flag as well as other flags spuriously. They do require the IEEE754 rounding direction attribute to be round-to-nearest-ties-to-even, which is the default. However, these advantages of the emulation code come at a significant cost: as we are going to see, the emulation code is on average 1.5 to 20 times slower than the FP-based algorithms. The emulation code also has the disadvantage of being rather complex. The precise rounding logic for round-to-nearest-ties-to-zero for example is quite complicated, which required extra care at its development to overcome its error-prone nature.

The statistical distribution of the number of cycles used by our algorithms (using \(10^6\) samples, with the distributions of the inputs described below) is given:

- for the augmentedAddition algorithms, in Figures 4a for Algorithm 6 (AA-Simple), 4b for Algorithm 7 (AA-Full), and 4c for the integer-based emulation of augmentedAddition;
- for the augmentedMultiplication algorithms, in Figures 5a for Algorithm 8 (AM-Simple), 5b for Algorithm 9 (AM-Full), and 5c for the integer-based emulation of augmentedMultiplication.

For each input sample, formed by an input couple \((x, y)\), the number of cycles is measured as follows: the function implementing one of our algorithms is run on \(x \) and \(y\). Its execution time is measured by reading off the x86 Time.
Step Counter with the rdtsc instruction before and after the execution of the function. Before reading the Time Step Counter, the CPU’s pipeline is serialized by executing a dummy cpuid instruction, which Intel documents as having this serialization effect. As the time measurements obtained by subtracting the before Time Step Counter’s value from the after counter’s value also include the time for pipeline serialization, execution of the rdtsc instruction and the function call itself, the same measurement is repeated with an empty function that has the same signature as the actual function to time. The empty function’s measured execution time is subtracted off the actual function’s measured execution time. This yields a raw execution time sample in cycles. All raw execution times that are less than 1 cycle are discarded and the timing procedure is repeated. The measurement yielding to positive raw execution times is repeated 100 times, an average and maximum value is computed. If the average value does not differ from the maximum value by more than a certain amount (typically 25%), the average value is taken as the execution time in cycles for this input sample \((x, y)\). The measurements are taken on a CPU not executing any other heavy jobs, after a preheating phase for the instruction cache. The Linux scheduler is configured to keep the process on one CPU core as long as possible. Core migration is anyway filtered out by our testing strategy as it yields either negative raw timings or raw timings that are clear outliers. Overall, 10^6 different samples are timed, which yields to the histograms illustrated in Figures 4 and 5 as well as the average values (averaging over all 10^6 inputs) reported in Tables V and VI.

The different input samples \((x, y)\) are produced as follows:

- The all cases input samples are produced with a pseudo-random number generator such that all signs, exponents and significands are uniformly distributed among all binary64 FP values \((x, y)\) that are finite numbers such that the resulting outputs \((a, b)\) are finite as well. The filtering of whether or not a candidate \((x, y)\) produces finite outputs \((a, b)\) uses our integer-based emulation code to compute \((a, b)\) out of the candidate \((x, y)\).
- The all simple cases input samples are produced by filtering from the set of the all cases samples the ones for which the simple FP-based Algorithms 6 and 8 produce bit-correct results (including correct signs for zeroes). The decision of whether or not a candidate sample \((x, y)\) is an all simple case is taken by comparing the output of the respective FP-based simple algorithm with the one of our integer-based emulation code.
- The halfway cases input samples \((x, y)\) are such that the respective outputs \((a, b)\) are finite FP numbers (zero and non-zero but no overflows) and \(x + y\) resp. \(x \times y\) is precisely in the middle between two binary64 FP numbers. They are produced as follows:
  - For addition in binary64, a 54 bit odd integer number \(N\) is produced\(^2\) along with a uniformly distributed exponent \(E\). A uniformly distributed split-point \(\sigma \in \{1, \ldots, 53\}\) is then produced. Using \(\sigma, N\) is cut into two parts which, along with \(E\) and \(\sigma\), yield to the exponents and significands of candidates \(x\) and \(y\). Half of the values \(x\) and \(y\) are swapped. The “cutting” process is not actually just a bit cut but done in such a way that both \(x\) and \(y\) can be both negative or positive.
  - For multiplication on binary64, two uniformly distributed 27 bit odd integers are produced along with uniformly distributed exponents. The candidate \((x, y)\) samples are checked for finiteness and whether or not they produce finite outputs \((a, b)\); all candidates that do not satisfy these constraints are filtered out.
- The halfway simple cases are obtained by filtering from the halfway cases the ones for which the simple FP-based algorithms produce correct result, similarly as to how the all simple cases are obtained.

The average timings are given in the first half of Table V for the augmentedAddition algorithms, and the first half of Table VI for the augmented Multiplication multiplication algorithms. In each of these tables, the second half gives average timings for halfway cases.

Concerning augmentedAddition, Algorithm 7 is slightly better than the integer-based emulation in the general case, and significantly better in the bad cases. Concerning augmented Multiplication, Algorithm 9 is significantly better, except on very rare cases (at the extreme right of Figure 5b). In all cases, the “simple” versions of the algorithms (Algorithms 6 and 8) are significantly faster in the cases when they work. They may also be significantly slower when they do not work, due to

\(^2\)This actually means that only 52 bits are random, as the 53rd bit and the 0th bit must be set.
TABLE V: Average timings in cycles for the augmentedAddition algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>% of cycles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm 6 (addition, all simple cases)</td>
<td>7.66</td>
</tr>
<tr>
<td>Algorithm 7 (addition, all cases)</td>
<td>10.46</td>
</tr>
<tr>
<td>Integer-based emulation of addition (all cases)</td>
<td>14.70</td>
</tr>
<tr>
<td>Algorithm 6 (addition, halfway simple cases)</td>
<td>7.74</td>
</tr>
<tr>
<td>Algorithm 7 (addition, halfway cases)</td>
<td>9.82</td>
</tr>
<tr>
<td>Integer-based emulation of addition (halfway cases)</td>
<td>4.99</td>
</tr>
</tbody>
</table>

TABLE VI: Average timings in cycles for the augmentedMultiplication algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>% of cycles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm 8 (multiplication, all simple cases)</td>
<td>7.62</td>
</tr>
<tr>
<td>Algorithm 9 (multiplication, all cases)</td>
<td>13.45</td>
</tr>
<tr>
<td>Integer-based emulation of multiplication (all cases)</td>
<td>75.65</td>
</tr>
<tr>
<td>Algorithm 8 (multiplication, halfway simple cases)</td>
<td>3.15</td>
</tr>
<tr>
<td>Algorithm 9 (multiplication, halfway cases)</td>
<td>4.99</td>
</tr>
<tr>
<td>Integer-based emulation of multiplication (halfway cases)</td>
<td>58.34</td>
</tr>
</tbody>
</table>

**CONCLUSION**

We have presented and implemented algorithms that allow one to emulate the newly suggested “augmented” floating-point operations using the classical, rounded-to-nearest ties-to-even, operations. The algorithms are very simple in the general case. Special cases are slightly more involved but will remain infrequent in most applications. These algorithms compare favorably with an integer-based emulation of the augmented operations. Furthermore, the availability of both tests for special cases and formal proofs covering normal and underflow cases (despite the limitations presented in Section V) gives much confidence in these algorithms.

**REFERENCES**


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