VirVarSeq: a low-frequency virus variant detection pipeline for Illumina sequencing using adaptive base-calling accuracy filtering

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ABSTRACT

Motivation: In virology, massively parallel sequencing (MPS) opens many opportunities for studying viral quasi-species, e.g. in HIV-1- and HCV-infected patients. This is essential for understanding pathways to resistance, which can substantially improve treatment. Although MPS platforms allow in-depth characterization of sequence variation, their measurements still involve substantial technical noise. For Illumina sequencing, single base substitutions are the main error source and impede powerful assessment of low-frequency mutations. Fortunately, base calls are complemented with quality scores (Qs) that are useful for differentiating errors from the real low-frequency mutations.

Results: A variant calling tool, Q-capeup, is proposed, which exploits the Qs of nucleotides in a filtering strategy to increase specificity. The tool is imbedded in an open-source pipeline, VirVarSeq, which allows variant calling starting from .fastq files. Using both plasmid mixtures and clinical samples, we show that Q-capeup is able to reduce the number of false-positive findings. The filtering strategy is adaptive and provides an optimized threshold for individual samples in each sequencing run. Additionally, linkage information is kept between single-nucleotide polymorphisms as variants are called at the codon level. This enables virologists to have an immediate biological interpretation of the reported variants with respect to their antiviral drug responses. A comparison with existing SNP caller tools reveals that calling variants at the codon level with Q-capeup results in an outstanding sensitivity while maintaining a good specificity for variants with frequencies down to 0.5%.

Availability: The VirVarSeq is available, together with a user’s guide and test data, at sourceforge:
http://sourceforge.net/projects/virtools/?source=directory

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Supplementary information: Supplementary data are available at Bioinformatics online.

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its weakness in the detection of low-frequency variants (Prosperi et al., 2013), whereas the latter is our main interest. Instead, we prefer to call variants within the read length to avoid challenges encountered in the haplotype reconstruction. On the other hand, linkage between the nucleotides is lost when calling variants at the SNP level. In this contribution, we introduce a novel strategy for calling variants at the codon level (nucleotide triplets), which facilitates immediate biological interpretations, particularly in virology applications where drug target regions are of interest.

In this article, we present an innovative approach for variant calling at the codon level, named Q-cpileup, that reduces the number of false-positive findings by exploiting the Qs of the nucleotides generated by sequencing. Our thresholding strategy is adaptive to provide an optimized threshold for individual samples in each sequencing run. Q-cpileup is imbedded in a pipeline, called VirVarSeq, which starts from fastq files.

2 METHODS

Several samples were sequenced using Illumina’s genome analyzer (GA) IIx according to manufacturing protocols (see Supplementary Material). The VirVarSeq pipeline proceeds as follows:

1. The sequenced reads are aligned against a reference sequence using the Burrows-Wheeler aligner tool (Li and Durbin, 2009).
2. Based on this alignment, a consensus sequence is defined.
3. A realignment is performed against this consensus. This strategy of iterative mapping will increase coverage, especially in samples where the consensus strongly deviates from the reference (see Supplementary Fig. S1).
4. After alignment, Q-cpileup is executed, which consists of a three-step analysis:
   a. In the first step, the Qs of the codons in the reading frame of interest are retrieved.
   b. Next, the threshold is determined dependent on the quality of the run.
   c. Finally, the filtered codon table is constructed.

The VirVarSeq pipeline, which runs from fastq to the filtered codon table, is available at http://sourceforge.net/projects/virtools/?source=directory together with a user’s guide (see Supplementary Material 2). All reads containing indel errors are removed before running Q-cpileup. It is hereby assumed that indels will result in non-viable virus. In some rare occasions, however, there might be an insertion mutation at the codon level, which can be investigated in a separate analysis (see indel Table Supplementary Material). Below, the different steps from Q-cpileup will be explained in more detail.

2.1 Quality of codons

A pileup of read bases is generated using the alignments to a consensus sequence. In analogy with mpileup of samtools, for which the base-pair information at each reference position is described, mpileup describes the codon information at each amino acid position of the reference genome. For each position in the reference genome, the different codons are reported together with one Q for each codon. This requires that the Qs of the three nucleotides within a codon have to be summarized. A comparative analysis of different summarizations revealed that the weakest link, i.e. minimum Q of the three nucleotides in the codon, provided the best separation between low- and high-quality codons (see Supplementary Fig. S2). This minimum Q represents the codon’s nucleotide with the highest probability of being a sequencing error. A codon table is built based on the pileup where for each codon position of the reference the different codons within a sample are reported together with their frequency (Table 1). The minimum Qs of the codons at a particular position are averaged to give a rough idea about the overall quality. However, the individual minimum Qs of the codons themselves is used in subsequent analyses.

2.2 Q-intersection threshold

The distribution of the minimum Qs was checked and compared for one particular sample sequenced in two different runs and three different lanes reaching an average coverage of around 30 000 (Fig. 1). The shape of the distributions can be approximated by a mixture distribution with three truncated normal components (see Supplementary Material for model selection and goodness of fit in Supplementary Fig. S3). Truncation is performed at the lower and upper ends of the Q range. The first mode represents a point probability at Q 2, which is the lowest Illumina Q. This is due to an artifact created by Illumina’s base caller. Read ends with a segment of mostly low quality (≤Q15) are given a Q of 2. The second component distribution is a distribution of low Qs, reflecting the sequencing error distribution. Finally, the highest mode, close to 40, originates from a distribution of reliable calls. Note that the mixture of three normal components for the errors and reliable calls should be considered only as a working assumption and that neither trimming nor filtering of the data is required before fitting the mixture models. The expectation maximization (EM) algorithm of McLachlan (McLachlan and Jones, 1988) will be applied for fitting these normal mixture models. We have written an R-wrapper to run the original Fortran code of McLachlan, which is embedded in the pipeline VirVarSeq. The EM algorithm was initialized by setting the three modes at 2, 10 and 35 and the variances at 0.8 for the point probability and 40 for the other two distributions. The marginal error probability, the sum of mixing proportion of the distributions at 2 and 10, was set to 15%.

The bulk of Qs was high, indicating a majority of reliable calls in the dataset (green distribution in Fig. 1). At the other end, a clear point probability at the Q of 2 was seen. The red distribution in Figure 1 corresponds to low-quality codons that are likely to be sequencing errors. There are several criteria to define a threshold for filtering the low-quality codons and for distinguishing between errors and reliable

<table>
<thead>
<tr>
<th>Position</th>
<th>Ref Codon</th>
<th>Codon</th>
<th>Count</th>
<th>Coverage</th>
<th>Frequency (%)</th>
<th>Mean Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>001</td>
<td>GGG</td>
<td>AGG</td>
<td>167</td>
<td>18 966</td>
<td>0.88</td>
<td>35</td>
</tr>
<tr>
<td>001</td>
<td>GGG</td>
<td>GTG</td>
<td>83</td>
<td>18 966</td>
<td>0.44</td>
<td>16</td>
</tr>
<tr>
<td>001</td>
<td>GGG</td>
<td>TGG</td>
<td>15</td>
<td>18 966</td>
<td>0.08</td>
<td>33</td>
</tr>
<tr>
<td>001</td>
<td>GGG</td>
<td>GGG</td>
<td>18 693</td>
<td>18 966</td>
<td>98.6</td>
<td>37</td>
</tr>
<tr>
<td>002</td>
<td>CGT</td>
<td>CAG</td>
<td>461</td>
<td>19 217</td>
<td>2.4</td>
<td>30</td>
</tr>
<tr>
<td>002</td>
<td>CGT</td>
<td>GGG</td>
<td>20</td>
<td>19 217</td>
<td>0.1</td>
<td>5</td>
</tr>
</tbody>
</table>

Notes. The different codons observed in a sample are counted at each codon position of the reference genome and their frequencies are calculated using the coverage at that particular position. The Qs are summarized by averaging the minimum Qs of the codons. Position: amino acid position of the reference. Ref: codon of the reference genome at a particular position. Codon: codon present in a sample at a particular position. Count: the number of times a particular codon occurs in the pileup at a particular position. Coverage: the number of reads that fully cover a particular codon position. Frequency: Count/Coverage. Mean: Average of the minimum Qs of a particular codon at a particular position.
2.3 Filtering of codon tables

Once the QIT is determined, an updated codon table can be constructed. All codons with a minimum Q below the threshold will be filtered from the analysis. The influence of trimming is negligible, as it mainly affects low-quality nucleotides, which are removed by the filter. The three-step analysis returns a codon table with different variants and their frequencies at each codon position of the reference, which is robust to sequencing errors.

3 RESULTS

3.1 HCV plasmid mixtures

To assess the filtering accuracy of Q-cpileup, we made use of two plasmids that carry HCV NS3 amino acids 1 to 181 and that differ at only two codon positions, 36 and 155. The two plasmids were mixed in four different proportions—1:10, 1:50, 1:100 and 1:200—and sequenced with average coverages of 96 211, 81 179, 95 590 and 74 820, respectively (see Supplementary Material for sample preparation; sequencing data are available at the European Nucleotide Archive, accession number PRJEB5028). A minor variant is defined as a codon that differs from the consensus. Hence, only two minor variants are expected at codon positions 36 [GTC (consensus) → ATG] and 155 [CGG (consensus) → AAA]; all others can be considered as false-positive findings. For each of the four sequenced mixes, the QIT was determined (Table 2). Comparison of the number of variants when no filtering but trimming (QIT = 0) is applied and after Q-cpileup reveals that adaptive quality filtering can reduce the number of false-positive findings by 20–50% (third and fourth columns of Table 2). With Q-cpileup, no false-positive findings are reported with frequencies >1%, a reporting limit defined by Thys et al. (Manuscript under review). This is in strong contrast with the 7–12% FDR without filtering, for discoveries with frequencies >1%. Q-cpileup is able to reduce the number of false-positive findings while the frequencies of the true minor variants (last columns of Table 2) remain unaltered.

The results for the mixing proportion of 1% are shown in more detail in Figure 2. A QIT of 19 was used for filtering in this sample (Fig. 2a). In panel b, the codons equal to the consensus (called major variants) are investigated before (QIT = 0) and after filtering (QIT = 19). The plasmid data have only two real variants, meaning that the codons investigated here should have frequencies close to 100%. After applying Q-cpileup, the frequencies of the codons are indeed closer to 100, indicating again that the number of false-positive findings is reduced. The minor variants are compared in panel c. Without filtering, several minor variants are reported with frequencies above the reporting limit of 1%. Their frequencies are strongly reduced after filtering, while the estimates of the true minor variant frequencies remain (red triangles). This suggests again that Q filtering provides effective noise reduction while still retaining the reliable calls at low frequency. Figure 2c reveals that our new filtering method allows for lowering the reporting errors.

Table 2. HCV plasmids results for 181 codon positions sequenced with average depth of 87 000

<table>
<thead>
<tr>
<th>Mix</th>
<th>QIT</th>
<th>N’ Variants</th>
<th>FDR (%)</th>
<th>Freq Codon 36 (%)</th>
<th>Freq Codon 155 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No filtering</td>
<td>Q-cpileup</td>
<td>No filtering</td>
<td>Q-cpileup</td>
</tr>
<tr>
<td>1:10</td>
<td>20</td>
<td>22 405</td>
<td>10 583</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>1:50</td>
<td>20</td>
<td>12 724</td>
<td>10 488</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>1:100</td>
<td>19</td>
<td>14 886</td>
<td>10 631</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>1:200</td>
<td>19</td>
<td>15 692</td>
<td>10 813</td>
<td>8</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: For each of four mixing proportions, the QIT is reported that was used for filtering. The number of reported codons, the false discovery rate for discoveries with frequency above 1% and the estimated frequencies of the true variants are compared before filtering is applied and after Q-cpileup.
false-positive findings with frequency
SNP caller in this comparison, but it also detects some
five SNPs at the 0.5% level, and only LoFreq could retrieve
part of Table 3. None of the methods could discover the
differ at five nucleotide positions, which should be discovered
mutations. The two codon variant positions present in the mixtures
on their capabilities for inferring diversity within viral popula-
tions. Hence, three SNP callers were chosen based
file with remapped reads against the reference region of inter-
problems (even after discussion with the developers) were
we were unable to use the original bam file, as unresolvable
limit, although the discovery of true variants below 0.5%
remains challenging.

3.2 Comparison with LoFreq, V-Phaser 2 and ShoRAH

The performance of Q-cpileup is compared with three other
methodologies: LoFreq (v0.5.0) (Wilm et al., 2012), V-phan-
er 2 (v2.0) (Macalalad et al., 2012) and ShoRAH (v0.8) (Zagordi
et al., 2011). They were run in their default settings and using
the previously described plasmid mixtures. With ShoRAH,
we were unable to use the original bam file, as unresolvable
problems (even after discussion with the developers) were
encountered when extracting the reads from the desired
region. Therefore, the ShoRAH results are based on a bam
file with remapped reads against the reference region of inter-
rest. None of the existing methods calls variants immediately at
the codon level. Hence, three SNP callers were chosen based
on their capabilities for inferring diversity within viral popula-
tions. The two codon variant positions present in the mixtures
differ at five nucleotide positions, which should be discovered
by the SNP callers. The results are presented in the top
part of Table 3. None of the methods could discover the
five SNPs at the 0.5% level, and only LoFreq could retrieve
all SNPs present at 1%. Hence, LoFreq is the most sensitive
SNP caller in this comparison, but it also detects some
false-positive findings with frequency >1% (bottom rows of

<table>
<thead>
<tr>
<th>SNP (WT)</th>
<th>LoFreq</th>
<th>V-Phaser 2</th>
<th>ShoRAH</th>
</tr>
</thead>
<tbody>
<tr>
<td>1:200</td>
<td>1:100</td>
<td>1:50</td>
<td>1:200</td>
</tr>
</tbody>
</table>

Table 3). Comparison with Table 2 reveals that the sensitivity
and specificity for discoveries >1% with Q-cpileup is outstand-
Especially its sensitivity is of utmost importance: the
method is initially developed for finding resistance-associated
mutations, and missing important variants might mislead fur-
ther treatment.

3.3 Clinical HCV sample and comparison with 454

Subsequently, Q-cpileup was applied on a clinical HCV sample
(see Supplementary Material for sample preparation). The fit
of the mixture distribution returned a QIT of 26 (Fig. 3a).
In Figure 3b, the frequencies of the codons before and after
filtering were plotted on the log scale, which allows a better
correlation of low-frequency variants. The frequencies of the
variants that were removed after filtering were indicated in
gray at the bottom. As the truth is unknown in clinical samples,
one cannot reliably separate true variants from sequencing
errors. However, one could compare the discovered variants
with 454 sequencing results. As 454 sequencing chemistry is dif-
fent, another error profile can be expected. Hence, variants
that were not discovered with 454 are more likely to be
Illumina sequencing errors (and vice versa) and are indicated
with red triangles in Figure 3b. A good correlation between the
filtered and the unfiltered variant frequencies is observed above
1%. The variants that were not detected in the 454 experiment,
likely to be false discoveries, drop in frequency after applying
Q-cpileup. Hence, our approach seems to control the false
discovery rate at a reasonable level up to variant frequencies of
0.5%. A lower coverage depth of the 454 experiment did
not allow for comparing Illumina and 454 sequencing for
frequencies <0.1%.
observed (indicated in red) is investigated in detail in Figure 5c.

located in a GC-rich region, where a coverage drop is

These maxima, however, are mainly originating from codons

depending on the lane on which it is sequenced. (Fig. 6a). In all, 83% of the samples report at most one add-

(454 sequencing were indicated with red triangles and are likely to be false-positive findings

The frequencies for all codons discovered on both lanes are

3.4 Effect of inter-/intra-run variability on QIT

An equimolar pool of 42 clinical HCV samples was sequenced

times to investigate the variability in sequencing quality

and hence the variability of the QIT. The 42 samples were

sequenced twice within the same run (R1) but on two different

lanes (L1 and L2), and they were all sequenced again in another

run (R2 L3). For one of these samples, the mixture distribution

of each of the three sequencing runs is shown in Figure 1. A clear
difference in quality between the runs is observed, resulting

in different QITs. Boxplots of the QITs of 42 samples for each

of the sequencing runs show that the inter-run variability

of the QIT is larger than the variability between lanes of the

same run (Fig. 4).

First, the effect of the intra-run variability of the QITs on the

final codon table was investigated. The number of reported
codons with frequency >1% is plotted for both lanes in Figure

5a. In all, 74% of the samples report at most one additional
codon, depending on the lane on which it is sequenced.

The maximum difference in reported number of codons is

four. We further explored frequency differences for all codons. The distribution of the differences in frequency between the two

lanes is plotted for each sample in Figure 5b. Overall, the

frequencies are similar with some deviations up to 3%.

These maxima, however, are mainly originating from codons

located in a GC-rich region, where a coverage drop is observed. The sample where the maximum absolute difference

is observed (indicated in red) is investigated in detail in Figure 5c.

In the next step, the inter-run variability of the QITs was

investigated. The second run was a high-quality run with fewer

errors (Fig. 1 comparing run 1 lane 2 and run 2 lane 3). The overall good quality in run 2 makes the estimation of the error

component of the mixture challenging and results in a large QIT.

The effect of these high QITs on the final codon table was inves-
tigated. The number of reported variants, with frequency >1%,
is again similar even after applying these high thresholds

(Fig. 6a). In all, 83% of the samples report at most one add-
tional variant, and only one sample reports four additional vari-
ants, which is again the maximum difference in reported number of variants. The distribution of the frequency differences

remains small overall, but the maximum difference in frequency as well as the relative change for these maxima rises (Fig. 6b and d).
Fig. 5. Effect of the intra-run variability of the QITs on the final reported codon frequencies. (a) Plot of the number of codons with a frequency >1% for the 42 samples sequenced on lane 1 (x-axis) and lane 2 (y-axis). The plotting symbols indicate the number of codons that differ between the two lanes. (b) Boxplots of differences in codon frequency between two lanes for each of the 42 samples. For each of the samples, 75% of the codons show differences in frequencies close to zero, whereas the upper whiskers range roughly between 0.5% and 3% difference in reported codon frequency, depending on the lane where the sample was sequenced. (c) Comparison of all codon frequencies on the log scale between two lanes for the sample where the maximum frequency difference is observed. The frequencies of codons not present in the other lane are plotted in gray. (d) Relative change for codons with maximum absolute difference plotted for each sample. The relative change is calculated as \( \frac{x_1 - x_2}{x_2} \) with \( x_1 \) and \( x_2 \) the codon frequencies for lane 1 and lane 2, respectively (sample with the maximum absolute difference in red). The sizes of the dots are scaled according to the estimated frequency in lane 1, indicating that most maximum differences occur at higher frequencies.

But these maxima occur again at rather high frequencies. When focusing on a particular sample, high QITs seem to have no negative impact on the final codon table (Fig. 6c). Despite the questionable working assumption that the second component separates the error distribution from the distribution of the reliable calls, the resulting QITs provide reliable codon tables. Hence, our filtering approach seems robust to deviations from the working assumption. Q-cpileup is adaptive and thereby can cope with differences in quality between runs.

3.5 Robustness of the method

Approximately 400 samples, from both HCV- and HIV-infected subjects, were sequenced in seven different runs and analyzed with Q-cpileup. Some examples of the HCV results are displayed in Figures 3 and 5. The sequenced amplicons of HCV samples cover GC-rich regions. It is known that Illumina is error prone in these regions (Dohm et al., 2008). This is reflected in the distribution of the minimum Qs where more low values are observed than with amplicons of HIV samples for which no GC-rich regions were covered (Supplementary Fig. S5). It is especially in these GC-rich regions where you expect that false-positive findings exist with frequencies >1% as seen in Figure 3b on the x-axis. When applying Q-cpileup, the frequencies of these false-positive findings could be reduced. In Supplementary Figure S5, we illustrate that the proposed strategy also similarly reduces the noise for HIV samples.

Although this new variant calling tool was primarily developed based on Illumina’s GAIIx sequencing data, it can also be a valuable tool for other Illumina sequencing platforms, such as HiSeq. HiSeq uses the same sequencing-by-synthesis technique and suffers from the same error types (Minoche et al., 2011). HiSeq data, analyzed with Q-cpileup, are presented in Supplementary Figure S6. The tool, however, is not applicable for pyrosequencing techniques, such as Roche 454. Their Qs do not reflect substitution error probabilities but probabilities of calling homopolymers of particular length (De Beuf et al., 2012). For these types of data, the tool...
can, however, still generate a codon table, but no threshold determination or QIT-based filtering should be applied.

4 DISCUSSION

Many sequence variant identification tools have been described in literature to call variants at the SNP level. Most approaches are tailored to call SNPs in human resequencing projects (Nielsen et al., 2011) where SNPs can be either heterologous (50%) or homologous (100%). However, in viral deep sequencing projects, the SNP frequency can vary between 100% and 0%, whereas SNPs present in <1% of the reads also may be of interest. Further, our main focus is the detection of drug-resistant variants for which a specific drug-target region has to be investigated. Hence, it would be beneficial to report variants at the codon level per amino acid position to enable an immediate biological interpretation of the variants with respect to their antiviral drug responses. Variant calling tools used by the virologists in this research field are either not fully described in-house tools (Noguera-Julian et al., 2013) or build based on SNPs (Parameswaran et al., 2012) at the DNA or RNA level only. In the latter case, one needs to retrieve the linkage information between the neighboring nucleotides to deduce effects at the coded amino acid level. This process is not always straightforward. Some of the variant callers developed for viral population sequencing have add-on tools, like V-profiler (Henn et al., 2012) for V-phaser (Macalalad et al., 2012), to convert the list of SNPs to a list of codon variants. However, these are mainly developed for 454 data. None of the available tools reports the variants immediately at the codon level. Therefore, Q-cPileup was initially developed and imbedded in a pipeline. By taking the weakest link as a representative for the quality of the codon, the filtering remains at the individual nucleotide level but reporting is done at the codon level. The approach is adaptive to allow for differences in quality between the runs.

The intersection point between the distributions of the errors and reliable calls is suggested as a threshold (QIT). However, other criteria could also be considered. For instance, the number of false discoveries can be controlled by defining the QIT as a certain quantile of the reliable call component distribution. By using the 5% quantile as a QIT, 5% of the codons, which are truly present in the population, are falsely considered as being errors. This statement relies heavily on the interpretation of the distributions as errors and reliable calls. However, the three-component mixture distribution should be considered only as a working assumption. Moreover, it is impossible to check the actual interpretation of the mixture distributions. Hence, the interpretation of the different components as error and reliable calls cannot always be warranted, particularly when low Qs are underrepresented. Therefore, we advise users to assess the distribution plots as diagnostic tools to critically judge whether the chosen threshold is acceptable and/or meaningful.

Instead of applying hard filtering with a QIT, as suggested in this article, the posterior probabilities of the reliable call distribution could be used. The counts of a codon at a particular position can be weighted with these probabilities. By doing so, codons with a low Q will have a low contribution in the final frequency estimates. Hence, data are not filtered but weighted with the probabilities of being truly present in the reliable codon population. This method also relies on the interpretation of the different component distributions as error distribution and reliable call distribution.

Importantly, we have shown that the filtering strategy using hard threshold QIT is robust to runs where the distributions deviate from the working assumption. The impact on the final codon table frequencies was minimal. Overall, our proposed filtering strategy controls the false-positive rate at reasonable levels with no false discoveries above a reporting limit of 1%. The noise is effectively reduced while retaining the reliable calls even at low frequency. This suggests that the reporting limit of detection at 1% could be lowered, although distinguishing true variants from error at 0.5% remains challenging. Depending on the risk one is willing to take to include a small number of false-positive findings, either one of the cutoffs can be used. More importantly, Q-cPileup shows a splendid sensitivity that could not be achieved by the SNP callers while maintaining a good specificity for variants with frequencies down to 0.5%. This sensitivity will allow further investigation of the reported variants above one of the cutoffs defined by the specificity to search for resistance-associated mutations, or in the next step to monitor drug resistance and guide treatment (Dierzynek et al., submitted for publication). Currently, the clinical cutoff is not yet defined for minority drug-resistant virus variants, and it is still a subject of open debate (Schneider et al., 2014). Some studies have found no significant association between the presence of low-frequency variants and subsequent virological failure, whereas others report clear correlations (Vanden Ende et al., 2014). The availability of methods that detect low-frequency variants at the codon level with high sensitivity and good specificity can help in defining the clinical benefit of low-frequency resistance testing.

5 CONCLUSION

A variant calling tool is proposed for identifying true variants at the codon level within a viral population using Illumina sequencing. The variants are filtered using base-calling Qs for reducing false-positive findings. The lowest Q of the three nucleotides of the codon is taken as representative for the codon. An adaptive strategy is developed to provide an optimized threshold for individual samples in each sequencing run. The intersection point of the component distributions of the mixture is suggested as a valuable threshold, QIT. Codons with a Q below this threshold are not reported. The robustness against deviations of the working assumption justifies the utilities of our method for low- and high-quality sequencing runs. It is shown that the generated filtered codon table is reporting far fewer false-positive findings compared with the codon table based on the raw data. Moreover, VirVarSeq has a superb sensitivity compared with existing SNP callers while maintaining a good specificity for codon variants with frequencies down to 0.5%. This suggests that the current reporting limit of detection at 1% can even be lowered. The tool is implemented in a user-friendly open-source pipeline, VirVarSeq, which allows virologists to call variants at the codon level starting from the fastq files.
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