

Accurate Genetic Detection of Hepatitis C Virus Transmissions in Outbreak Settings

David S. Campo, Guo-Liang Xia, Zoya Dimitrova, Yulin Lin, Joseph C. Forbi, Lilia Ganova-Raeva, Lili Punkova, Sumathi Ramachandran, Hong Thai, Pavel Skums, Seth Sims, Inna Rytsareva, Gilberto Vaughan, Ha-Jung Roh, Michael A. Purdy, Amanda Sue, and Yury Khudyakov

Molecular Epidemiology and Bioinformatics Laboratory, Division of Viral Hepatitis, Centers for Disease Control and Prevention, Atlanta, Georgia

Hepatitis C is a major public health problem in the United States and worldwide. Outbreaks of hepatitis C virus (HCV) infections are associated with unsafe injection practices, drug diversion, and other exposures to blood and are difficult to detect and investigate. Here, we developed and validated a simple approach for molecular detection of HCV transmissions in outbreak settings. We obtained sequences from the HCV hypervariable region 1 (HVR1), using end-point limiting-dilution (EPLD) technique, from 127 cases involved in 32 epidemiologically defined HCV outbreaks and 193 individuals with unrelated HCV strains. We compared several types of genetic distances and calculated a threshold, using minimal Hamming distances, that identifies transmission clusters in all tested outbreaks with 100% accuracy. The approach was also validated on sequences obtained using next-generation sequencing from HCV strains recovered from 239 individuals, and findings showed the same accuracy as that for EPLD. On average, the nucleotide diversity of the intrahost population was 6.2 times greater in the source case than in any incident case, allowing the correct detection of transmission direction in 8 outbreaks for which source cases were known. A simple and accurate distance-based approach developed here for detecting HCV transmissions streamlines molecular investigation of outbreaks, thus improving the public health capacity for rapid and effective control of hepatitis C.

Keywords. HCV; outbreak; threshold; NGS; nucleotide diversity; phylogenetic analysis; hamming distance; transmission networks.

Hepatitis C virus (HCV) infects nearly 3% of the world's population and is a major cause of liver disease worldwide [1]. HCV infection is an important US public health problem because it is the most common chronic blood-borne infection and the leading cause of the need for liver transplantation [2]. Since 2007, HCV infection has caused a greater annual number of deaths than HIV infection in the United States [3]. It is estimated that 2.7–3.9 million people in the United States have chronic HCV infection and that >15 000 die each year from HCV-related disease, with mortality expected to rise in the coming years [4]. Approximately 80% of patients who become infected with HCV develop chronic infections and are at risk for advanced liver disease; 15%–30% of these patients progress to liver fibrosis and cirrhosis, and up to 5% die from liver failure due to cirrhosis or hepatocellular carcinoma [2].

Outbreaks of HCV infections are associated with unsafe injection practices, drug diversion, and other exposures to blood and blood products. During 2005–2013 in the United States, 18 healthcare-associated outbreaks were detected, involving 228

outbreak-associated cases and >92 550 at-risk persons notified for screening. Of these, 9 outbreaks occurred in outpatient facilities, 7 occurred in hemodialysis settings, and 2 were caused by HCV-infected healthcare providers who were diverting drugs [5]. Considering that HCV has a long incubation period of up to 6 months and that HCV infection is asymptomatic in >70% of infected persons, the detected hepatitis C outbreaks most likely account for a fraction of outbreaks of HCV infections, resulting in the underidentification of recent transmissions and new cases of infections.

Several molecular approaches have been developed for tracking viral infections [6–15]. Over the past decade, our laboratory investigated numerous outbreaks of viral hepatitis in the United States, using molecular analysis (Supplementary Information) [16–22]. Molecular detection of viral transmissions is usually aided by phylogenetic analysis, during which a small viral genomic region is amplified and sequenced directly and a single sequence per case is used to construct a phylogenetic tree. The identification of transmission clusters from phylogenetic trees is achieved using several criteria. For example, a phylogenetic cluster of sequences can be interpreted as representing a single viral strain shared by cases involved in an outbreak if (1) genetic or patristic distances among sequences from the cluster are below a certain threshold and (2) the ancestral node for the suspected transmission cluster in the tree has a high statistical significance calculated using Bayesian statistics or bootstrap analysis. If available, data on sharing known association factors

Received 15 August 2015; accepted 8 October 2015.

Correspondence: D. S. Campo, Molecular Epidemiology and Bioinformatics Laboratory, Division of Viral Hepatitis, Centers for Disease Control and Prevention, Atlanta, GA 30333 (fyv6@cdc.gov).

The Journal of Infectious Diseases®

Published by Oxford University Press for the Infectious Diseases Society of America 2015. This work is written by (a) US Government employee(s) and is in the public domain in the US. DOI: 10.1093/infdis/jiv542

such as a close geographical location and high-risk behavior among members of the cluster can be used to evaluate the phylogenetic inferences [14]. Such approaches are commonly used in HIV forensics [23].

Although a single consensus viral sequence from each infected case is usually used for the molecular detection of outbreaks [14], the use of such sequences is not satisfactory for the accurate identification of viral strains because viruses, especially RNA viruses such as HCV, exist as a heterogeneous population of closely related but genetically distinct variants, known as quasispecies, in each infected person [24]. Such a population cannot be adequately represented with a single sequence. Moreover, considering that HCV infections are frequently established by minority variants transmitted from the source [20, 25], a consensus sequence cannot reliably capture such transmissions.

The limitations of consensus sequencing were solved by sequencing intrahost viral variants isolated by the end-point limiting-dilution (EPLD) technique [26] and, recently, by next-generation sequencing (NGS) [27, 28]. A large sample of intrahost viral variants obtained using NGS represents more adequately intrahost viral subpopulations and their minority variants, thus, improving the accuracy of genetic detection of transmissions [27, 29, 30]. However, sampling thousands of intrahost HCV variants complicates phylogenetic analysis, straining computational resources, being time-consuming and yielding dense trees that are difficult to interpret. Given the need for a rapid response during HCV outbreaks, a simple and accurate approach to the detection of HCV transmissions by NGS data would be very useful.

Here, we have developed and validated a method for the molecular detection of HCV outbreaks. A simple, accurate and fast distance-based method for the detection of cases linked by transmission was devised using sequence data obtained from cases identified during epidemiologically curated HCV outbreaks. In addition, we found that, in 8 outbreaks with a known HCV infection source, this source can be accurately identified using the population-level nucleotide diversity.

METHODS

Related Samples

Sequences of HVR1 were obtained from 127 cases collected during 32 epidemiologically defined outbreaks (see [Supplementary Information](#) and elsewhere [16–22] for a complete list). HCV from 76 cases belonged to genotype 1a, and HCV from 51 cases belonged to genotype 1b. All outbreak-associated HCV infections were serologically confirmed and epidemiologically defined as described previously [5]. Outbreak-associated HCV infections are defined as those with serological, clinical, and epidemiologic evidence supporting transmission and include infections identified during the acute phase or previously undiagnosed chronic infections with epidemiologic evidence indicating that these were likely outbreak-related incident

cases that progressed from the acute to the chronic stage [5]. The source case of HCV infection was known for 8 outbreaks [16–22]. The HCV strain identified in one of the outbreaks (AW) [22] was additionally sequenced from all 18 cases, using NGS. For more details of each outbreak and sequence access, the authors of each cited article should be contacted.

Unrelated Samples

Two sets of HCV sequences obtained from epidemiologically unrelated individuals were used in the study. Sequences from 193 HCV infected individuals were obtained by EPLD PCR, using serum specimens from national collections [31, 32] and other surveillance projects conducted in the laboratory. HCV from 118 individuals belonged to subtype 1a, and those from 75 belonged to subtype 1b. A second set of sequences was obtained by NGS from 221 HCV-infected patients, with 81 infected with HCV subtype 1a, 41 infected with subtype 1b, 58 infected with genotype 2, 39 infected with genotype 3, and 2 infected with genotype 4. Some of these samples were described previously [28] and gathered from other surveillance projects conducted in the laboratory.

EPLD Real-Time PCR

Total nucleic acids from the specimens were extracted from serum, and RNA was precipitated and underwent reverse transcription using both random and specific primers as previously described [26]. We used the EPLD PCR protocol for sequencing multiple clones of HVR1, as previously described [26, 33].

NGS

PCR products were pooled and subjected to pyrosequencing using the Junior GS or GS FLX Titanium Sequencing Kit (454 Life Sciences, Roche, Branford, Connecticut). The NGS files were processed using the error correction algorithms KEC and ET [34].

Data Analysis

For each sample of HCV sequences, a multiple sequence alignment (MSA) was created using MAFFT 7.221 [35]. The primer sequences were removed, and the final sequences were 264 nucleotides in length. The level of genetic heterogeneity of each sample was estimated by calculating the nucleotide diversity (π) in accordance with previously published methods [36, 37], using MATLAB R2014a [38]. The sequences of every pair of samples were aligned and used to calculate genetic distances with MATLAB [38]. A maximum likelihood tree was constructed with MEGA 6, using the Nei–Tamura substitution model [39]. Patristic distances were calculated over the phylogenetic tree, using MATLAB [38]. For each distance type, we measured the overlap between the distributions of values among related or unrelated samples, using the Bhattacharyya coefficient, which is equal to 0 when 2 distributions do not overlap and equal to 1 when they completely overlap [40].

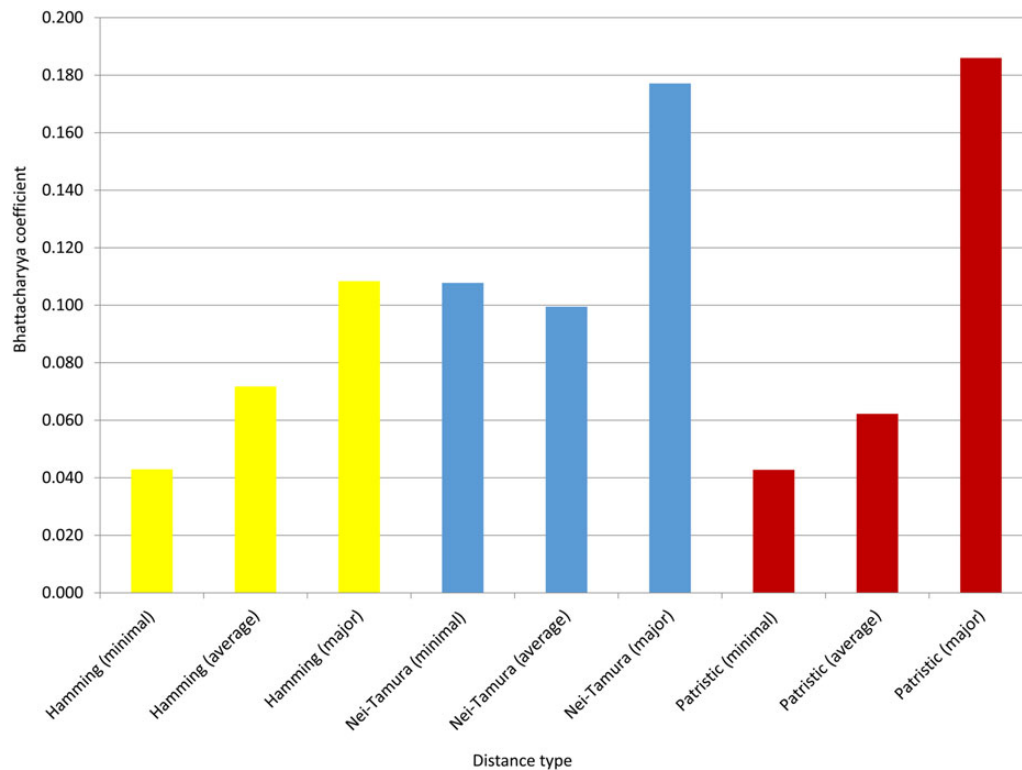


Figure 1. Overlap between the distributions of distances among related or unrelated samples.

Transmission Network

A transmission network that represents the genetic relatedness between samples was built using MATLAB [38] and was drawn with GEPHI [41].

k-step Network

For one of the outbreaks (AW), we built a k-step network, as we previously described [28]. The k-step network contains all possible minimum spanning trees and allows for efficient visualization of the genetic relatedness among all haplotypes present in the sample. The networks were drawn with GEPHI [41].

RESULTS

Intrahost HCV Populations

A total of 12 987 HCV clones obtained using EPLD PCR were analyzed in this study. These HCV clones were obtained from 320 HCV-infected cases. On average, each sample contained 40.58 clones, with 21.52 being different (hereafter referred to as “HCV variants”); a major variant representing 34% of all clones; and a hamming distance of 2.58%.

Genetic Distances Among Samples of HCV Sequences

There were 374 pairwise comparisons among samples belonging to the same transmission cluster from 32 epidemiologically confirmed outbreaks, of which 78 (20.86%) were between identical HCV variants and 73 (19.52%) were between HCV variants that differ at a single nucleotide position. Although the

sharing of identical variants among samples is strong evidence of direct transmission, not all epidemiologically linked samples share HCV variants, indicating a need in a less stringent threshold to accurately define transmission clusters. To establish this threshold, we studied the distribution of pairwise distances among samples belonging to the same outbreak (related) and samples without any epidemiological linkage (unrelated).

Table 1. Descriptive Statistics of the Studied Samples, by Hepatitis C Virus Genotype

Variable	1a	1b	Overall
Samples, no.	194	126	320
Outbreaks, no.	20	12	32
Related samples, no.	76	51	127
Unrelated samples, no.	118	75	193
Pairwise related, no.	165	209	374
Pairwise unrelated, no.	6903	2775	18 528
Related distance, mean \pm SD	0.87 \pm 1.21	1.14 \pm 1.48	1.02 \pm 1.37
Unrelated distance, mean	12.97	15.04	20.60
Ratio of mean unrelated to mean related distances	14.91	13.19	20.20
Pairwise related distances greater than threshold, no.	2	6	8
Pairwise unrelated distances less than threshold, no.	0	0	0
Missed outbreak samples, no.	0	0	0

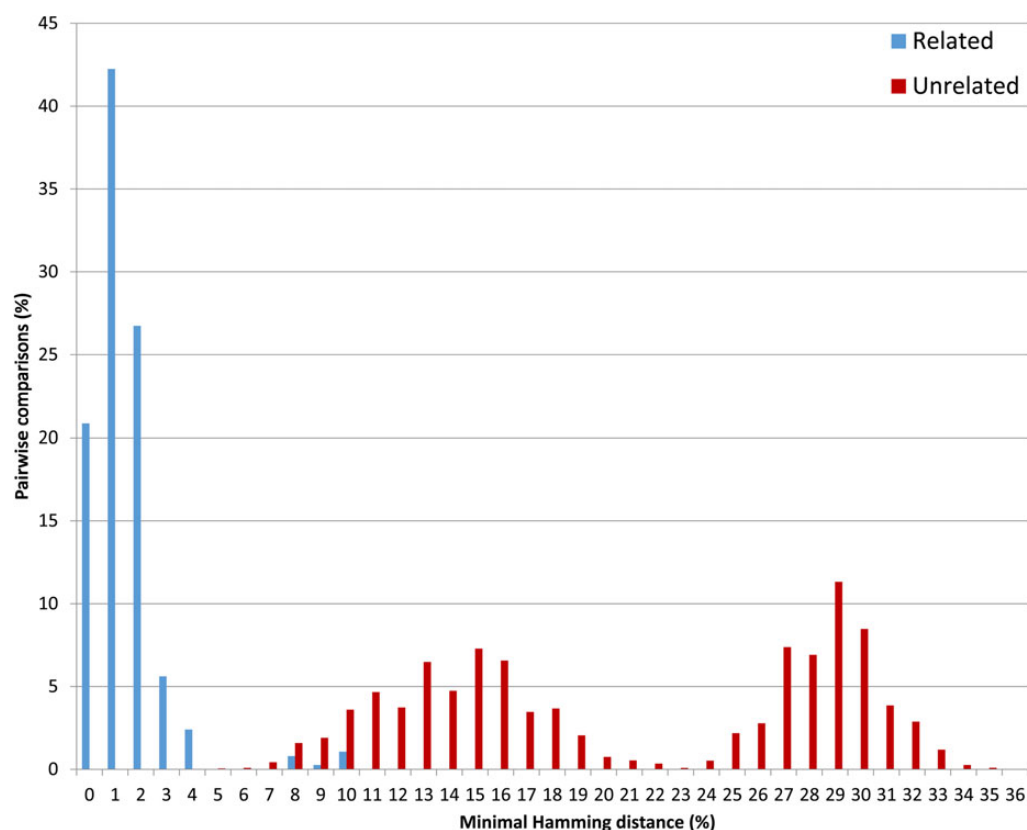


Figure 2. Distribution of pairwise distances. Percentage of pairwise comparisons for each category of minimal Hamming distance.

Three forms of genetic distances were considered: (1) Hamming distance, which is the number of mismatches; (2) Nei–Tamura distance, which takes into account transitions and transver-

sions; and (3) patristic distance, which is calculated over the branches of the maximum likelihood phylogenetic tree. Given that each sample includes a population of variants, 3 different

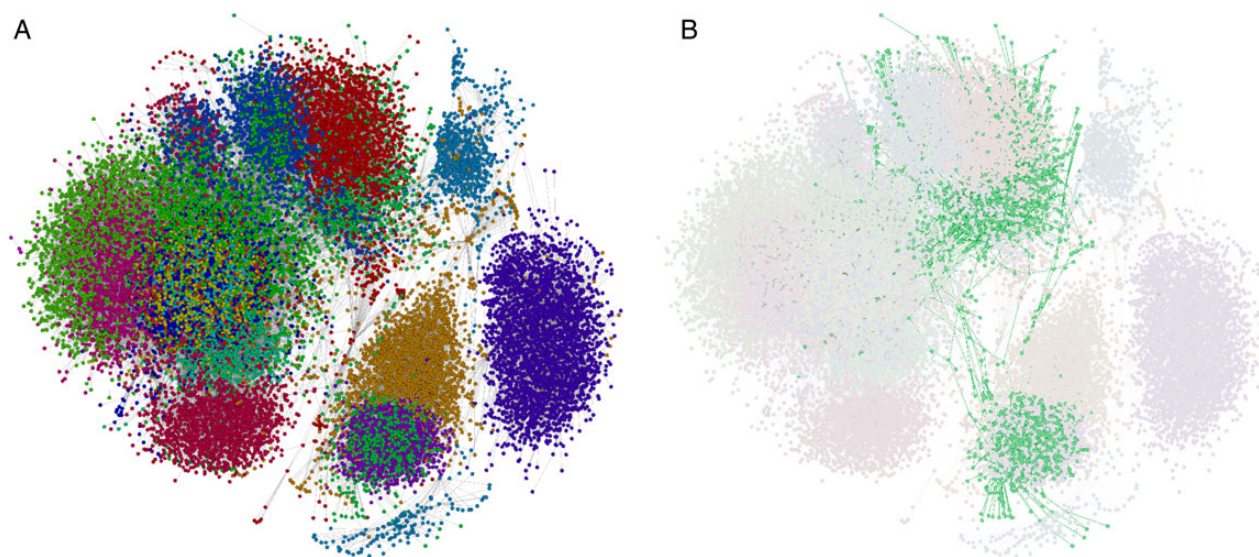


Figure 3. *A*, k-step network of the hepatitis C virus (HCV) variants sampled during a single outbreak (AW). The k-step network contains all possible minimum spanning trees and allows efficient visualization of the genetic relatedness among all variants. Each node is an HCV variant, and different cases are shown in different colors. *B*, The same k-step network, with the HCV variants present in the source highlighted in green. This figure is available in black and white in print and in color online.

measures were used for each distance: (1) the minimal distance among all possible pairs of variants between 2 samples; (2) the average distance; and (3) the distance between major variants from each sample. The last measure was included to simulate the situation in which a single sequence per sample was obtained, as is often the case in several molecular epidemiology studies.

For each distance type, we measured the overlap between the distributions of values among related or unrelated samples (Figure 1), using the Bhattacharyya coefficient. Among the distances, the minimal distance was superior, which is in agreement with the observation that minority variants are frequently responsible for transmission [20, 25]. The overlap between the distributions was approximately 2.8 times greater than that for the minimal distance. Overall, the minimal Hamming and minimal patristic distances were equal in performance, with both showing the same overlap values (Bhattacharyya coefficient, 0.043) and being highly correlated ($r = 0.992$).

A Relatedness Threshold

Considering performance and simplicity, the minimal Hamming distance was selected to find a threshold for the most accurate separation of the related and unrelated samples (Table 1). Figure 2 shows that the distributions of minimal Hamming distances among related and unrelated samples were very distinct. The threshold of 3.77% was calculated as the average minimum distance among the related samples (1.02%) plus 2 standard deviations (1.37%). This threshold was lower than any of the 18 528 unrelated pairwise distances and greater than all but only 8 (2.14%) of the related pairwise distances. Although some distances between related cases were greater than this threshold, all 127 outbreak samples were found linked to ≥ 1 case from the corresponding transmission clusters. Thus, the relatedness threshold yielded 100% sensitivity and 100% specificity in the detection of cases involved in these outbreaks.

Application of the Threshold to NGS Data

The threshold was established using the data generated by EPLD PCR. However, NGS provides an opportunity to sample many more intrahost viral variants, which may affect the threshold accuracy. To assess the applicability of the threshold to NGS data, we studied a second independent set of HCV HVR1 sequences obtained by NGS from 221 unrelated cases. Among all possible 24 310 pairwise comparisons, not a single distance was below the established relatedness threshold, indicating a strong specificity of the threshold applied to the NGS data. In addition, the NGS data were obtained for 18 cases involved in the AW outbreak (Figure 3A and 3B). Analysis of the data identified the same transmission cluster, but NGS yielded an approximately 4-fold increase in the number of links among related cases sharing identical sequences as compared to EPLD PCR (60.13% vs 14.38%). This increase indicates that a greater sampling of intrahost HCV variants improves the sensitivity of the transmission detection by increasing the probability of

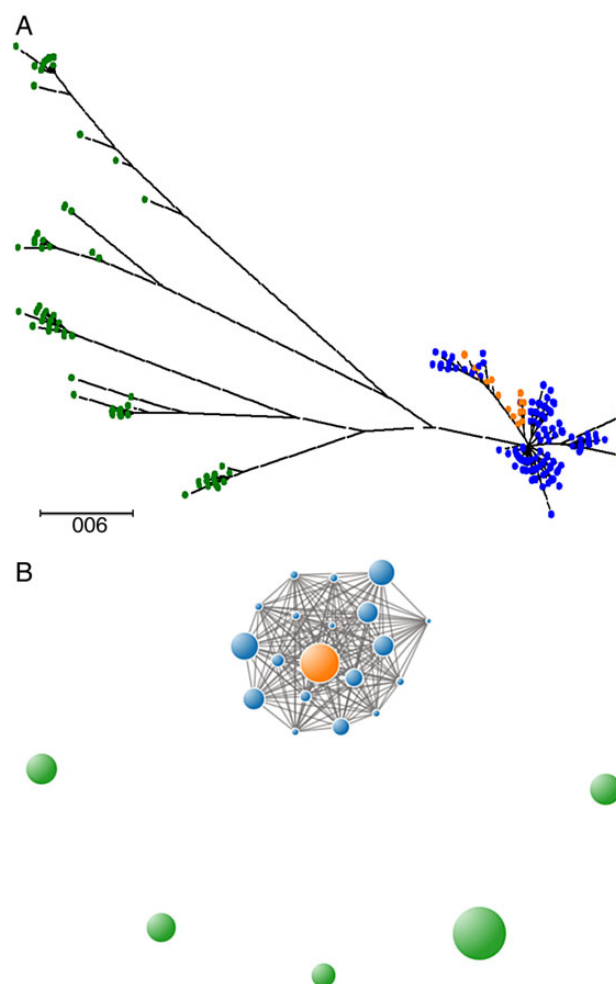


Figure 4. A, Phylogenetic tree of hepatitis C virus (HCV) variants sampled during a single outbreak (AW) [42]. Each leaf is an HCV variant. Green nodes represent sequences obtained from 5 unrelated cases, blue nodes represent those from 18 incident cases, and orange nodes represent those from the known source of the outbreak, a drug-diverting, HCV-infected surgical technician. B, Transmission network of the same outbreak (AW). Each node is an HCV sample. A link is drawn if the minimal Hamming distance between the 2 samples is smaller than the relatedness threshold (3.77%) and the size of the node is proportional to the sample nucleotide diversity. Green nodes represent unrelated cases, blue nodes represent related cases, and orange nodes represent the known source of the outbreak. This figure is available in black and white in print and in color online.

finding more-closely related or even identical HCV variants from outbreak-associated cases, using the relatedness threshold.

Transmission Graphs

A usual representation of the relatedness among sequences is a phylogenetic tree, which often requires considerable expertise for its construction and interpretation (Figure 4A). However, when the size of the data increases, the tree becomes unwieldy and may obscure a visual identification of transmission clusters. Here the calculated threshold allows for a graphical representation that captures the public health information in the more intuitive form of transmission networks. Figure 4B shows the

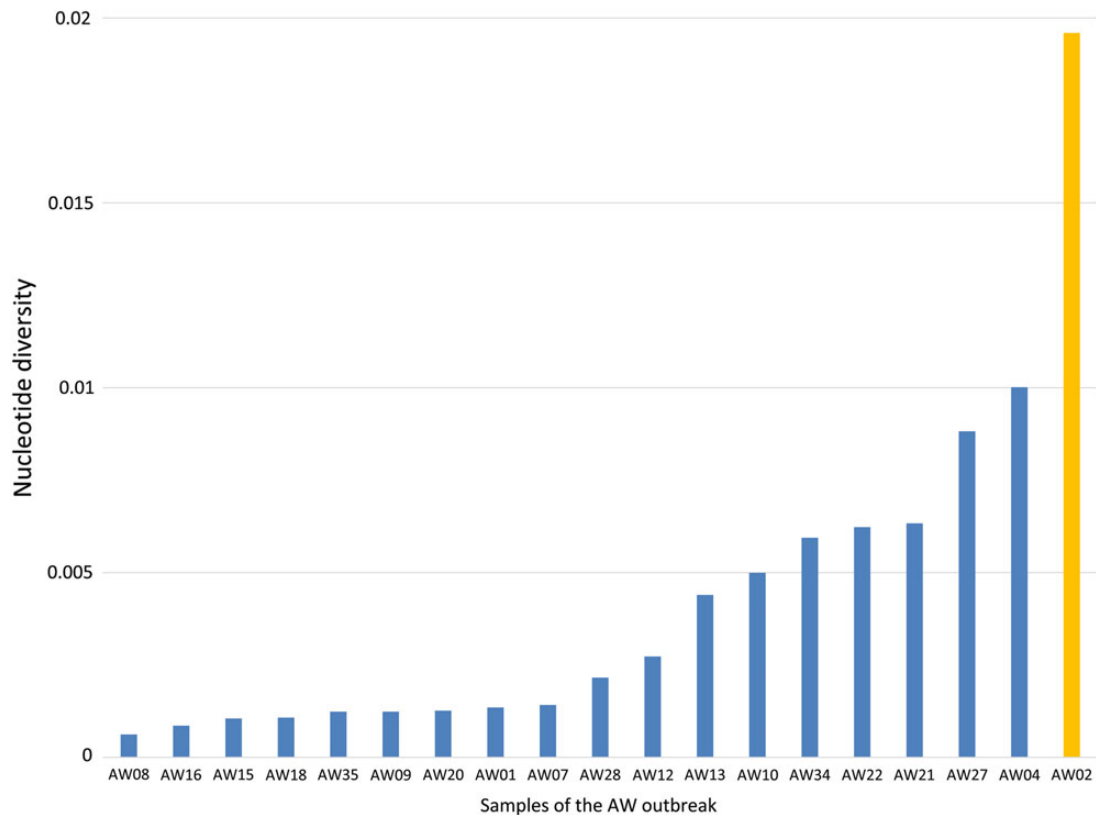


Figure 5. Hepatitis C virus (HCV) nucleotide diversity of each sample from the AW outbreak. The source of the outbreak (a drug-diverting, HCV-infected surgical technician) is shown in orange. This figure is available in black and white in print and in color online.

HCV HVR1 genetic relatedness data obtained from the AW outbreak as a network, taking the same data set used to generate the phylogenetic tree shown in Figure 4A. In this network, each node is an HCV sample; a link is drawn if the minimal Hamming distance between the 2 samples is smaller than the relatedness threshold (3.77%) and the size of the node is proportional to the nucleotide diversity of the intrahost viral population.

Source Identification

The epidemiologically identified source of HCV infections was known for 8 outbreaks, which were studied further in detail. Intrahost HCV populations sampled from the known source were found to be the most genetically heterogeneous among all cases involved in the corresponding transmission cluster. The level of genetic heterogeneity of each sample was measured by calculating the nucleotide diversity, as shown in Figure 5 for the AW outbreak. On average, over all 8 outbreaks, the source HCV population had 6.2 times greater nucleotide diversity than its associated incident cases and 4.3 times greater diversity than the incident case with the highest nucleotide diversity (Figure 6).

DISCUSSION

The presented approach identified accurately all transmission clusters in the tested outbreaks, separated these clusters from

epidemiologically unrelated HCV strains, and did not link any unrelated cases by transmission. The genetic linkage identified using the threshold approach developed here cannot be unambiguously interpreted as a direct transmission event without epidemiological data supporting such direct transmissions. Rather, our approach detects whether 2 patients share same HCV strain, and it should be interpreted as sampling from members of transmission chains or networks. Outbreaks are usually identified as a cluster of cases in certain epidemiological settings. Thus, identification of strain sharing among cases involved in such a cluster is a strong indication of linkage by transmission. However, this approach should be used with caution in investigation of transmissions that have occurred in the distant past because of the uncertainty of HCV evolution in a succession of hosts or over a long time.

Availability of extensive genetic data from outbreaks, as reported here, is unusual. However, certain information on genetic strain identity can be obtained from analyzing intrahost viral heterogeneity [43, 44]. The essential limitation of this approach, however, is its focus on intrahost rather than interhost viral evolution. Although both play an important role in defining viral genetic identity, transmission is largely an interhost process, and genetic heterogeneity associated with the transmitted viral strain cannot be accurately measured without consideration of

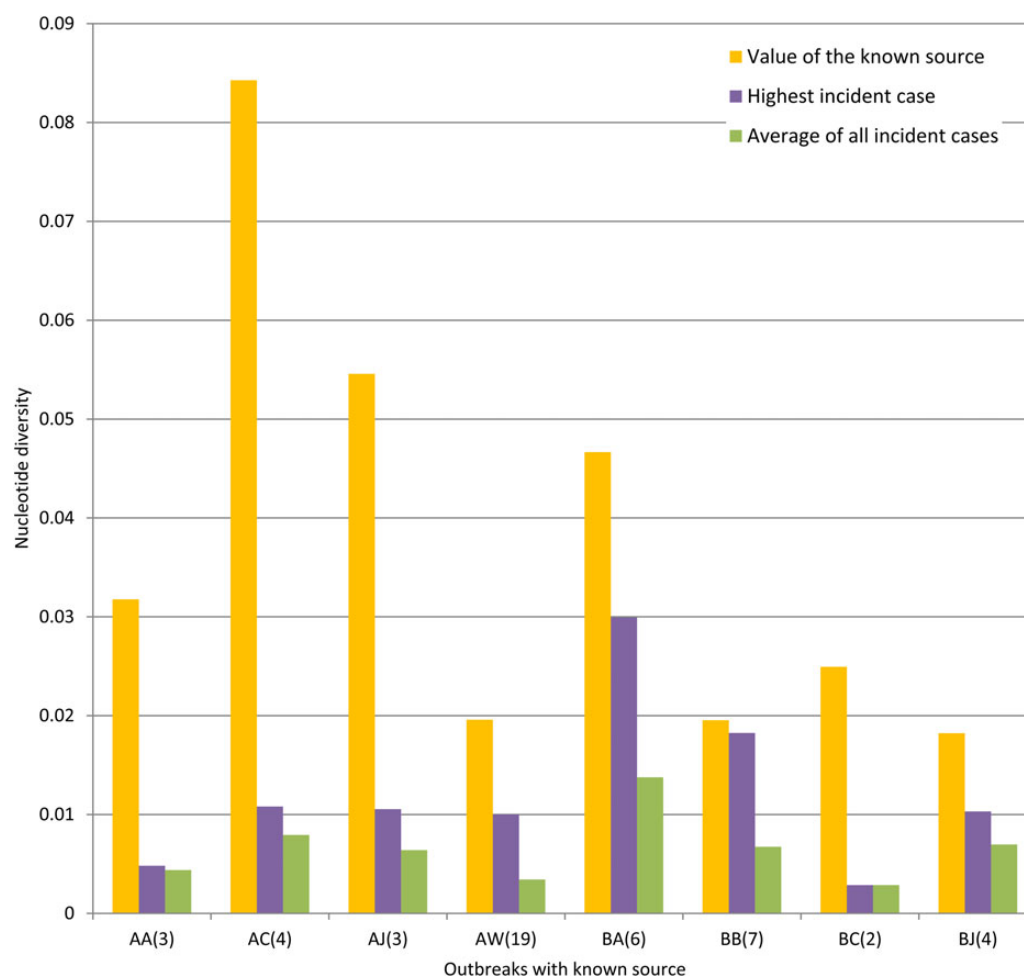


Figure 6. Nucleotide diversity of hepatitis C virus (HCV) hypervariable region 1 (HVR1) from the source and incident cases. The diversity of HCV HVR1 from the known source in each outbreak is shown in orange. The highest value of HVR1 nucleotide diversity found among incident cases is shown in purple. The average HVR1 nucleotide diversity from incident cases is shown in green. The total number of cases in each outbreak is shown in parenthesis. This figure is available in black and white in print and in color online.

intra-host and inter-host genetic changes. The approach implemented here takes into consideration both, measuring minimal genetic distances among viral populations of patients infected from a common source. The average Hamming distance among intra-host variants measured in our samples was 2.58%, which is lower than the relatedness threshold (3.77%) identified here. Application of the average value as a threshold would allow for separating all unrelated cases but also would lead to misclassification of 7.48% of related cases, thus reducing the sensitivity of transmission detection.

Although simple and efficient in outbreak settings, this threshold approach is very specific to the virus and genomic region used for the detection of transmissions, and it needs to be experimentally established for each pathogen or genomic region. A generalized approach that could have been readily applicable to different pathogens and genomic regions of the same pathogen would have significant advantages over the targeted threshold approach in detection of transmissions. The develop-

ment of such approaches exploiting different clustering techniques promises a more universal detection of transmissions [44, 45].

Simplicity of identification of a single sequence per specimen prompted application of consensus sequences to the detection of transmissions by phylogenetic analysis [14]. However, this study shows that genetic distances among HCV strains using a single sequence result in less accurate separation of related and unrelated cases. Moreover, consensus sequences obtained by direct sequencing are rarely identical to that of the major variant and are frequently different from that of any sequence variant sampled from a specimen [29, 33], indicating that consensus sequences result from amalgamation of a heterogeneous viral population and should be used with caution for the detection of transmission.

The accuracy of detection depends significantly on sampling of the sufficient number of intra-host viral variants to capture minority populations, which can be achieved with NGS [27, 28, 46]. In general, it can be expected that increases in the

number of variants sampled from intrahost viral populations should not change significantly minimal Hamming distances among HCV variants from epidemiologically unrelated cases, whereas minimal genetic distances among epidemiologically related HCV variants may become shorter owing to the greater probability of sampling minority variants. Indeed, as we observed in this study, the threshold approach developed using the EPLD PCR data performed equally well on NGS data obtained from unrelated HCV cases, but NGS data showed an improved sensitivity in the detection of transmission links among members of the transmission cluster in the AW outbreak.

Several types of distances were studied here, with the minimal Hamming distance identified as one of the most accurate for the detection of transmissions and as convenient to calculate. Although identical to the patristic distance with respect to the accuracy of transmission detection, as shown here, Hamming distance has an advantage in its simplicity. Hamming distance is computationally less intensive than the other distances and can be calculated rapidly even for large NGS data sets. Minimal distances are highly suitable for detecting recent viral transmissions, especially considering that HCV infections are frequently established by only some of the populations present in the source [20, 25].

With the predominance of phylogenetic analyses for identifying transmission clusters, the usual graphical representation of a transmission cluster uses a phylogenetic tree. However, a network representation is more suited for the threshold analysis developed here, showing potential transmissions among cases directly and streamlining interpretation of results. The graph is simple and can be easily modified if additional cases are added, without the need to recalculate distances among all previously studied cases, thereby considerably reducing computational time. This is in contrast with phylogenetic reconstructions, which need to be recalculated after adding new sequences, a significant burden in the current NGS period. Further, such graphs can be constructed using any type of validated genetic distances (eg, distances among mass-spectrometric profiles, as was shown earlier in our laboratory [42]). Finally, the current approach allows the implementation of very efficient computational algorithms to remove patient pairs that cannot have sequences with a distance below the threshold, reducing considerably the demand on computational resources [47].

Identification of the source of infection is crucial for the interruption and prevention of outbreaks. In general, HCV accumulates mutations during intrahost evolution and becomes more genetically heterogeneous [32, 48]. Thus, the difference in duration of infection between the source and incident cases can be explored for the detection of the transmission direction. Indeed, analysis of HCV cases from 8 outbreaks with known sources of infection showed that the source is infected with a much more diverse HCV population than any incident case from the corresponding transmission cluster. This finding is

supported with our earlier observation that the intrahost HVR1 nucleotide diversity is 1.8 times greater in patients with chronic than acute HCV infection [32, 49]. However, the difference in the genetic diversity allows for the accurate identification of the transmission direction only when the source was sampled. Otherwise, the incident case with the most heterogeneous HVR1 population may be classified as a source of infection in a transmission cluster. One possible way to resolve this issue is to establish a threshold, but its definition requires a greater number of outbreaks with a known source. These problems of transmission-direction detection have been noted earlier [23, 50] and warrant further investigation.

This simple and accurate distance-based approach for detecting HCV transmissions developed here streamlines molecular investigation of outbreaks, thus improving the public health capacity for a rapid and effective control of hepatitis C. Currently, the approach is one of the tools of the Global Hepatitis Outbreak and Surveillance Technology, which enables molecular outbreak investigation by an automated analysis of HCV sequences and graphical presentation of results (to be described elsewhere in detail).

Supplementary Data

Supplementary materials are available at <http://jid.oxfordjournals.org>. Consisting of data provided by the author to benefit the reader, the posted materials are not copyedited and are the sole responsibility of the author, so questions or comments should be addressed to the author.

Notes

Acknowledgments. We thank all researchers who contributed over the last decade to the outbreak investigations referenced here, especially the members of the Epidemiology and Surveillance Branch, Division of Viral Hepatitis, Centers for Disease Control and Prevention (CDC); and Chris Lynberg (Information Technology Services Office, Research and Development, CDC), Max Mirabito, Silver Wang, Robin Tracy, and Thom Sukalac (National Center for HIV/AIDS, Viral Hepatitis, STD, and TB Prevention Informatics Office, CDC), for their constant computational help.

Financial support. This work was supported by the Advanced Molecular Detection Program, Office of Infectious Diseases, CDC.

Potential conflicts of interest. All authors: No reported conflicts. All authors have submitted the ICMJE Form for Disclosure of Potential Conflicts of Interest. Conflicts that the editors consider relevant to the content of the manuscript have been disclosed.

References

1. Mohd Hanafiah K, Groeger J, Flaxman AD, Wiersma ST. Global epidemiology of hepatitis C virus infection: new estimates of age-specific antibody to HCV seroprevalence. *Hepatology* 2013; 57:1333–42.
2. Alter M. Epidemiology of hepatitis C virus infection. *World J Gastroenterol* 2007; 13:2436–41.
3. Ly KN, Xing J, Klevens RM, Jiles RB, Ward JW, Holmberg SD. The increasing burden of mortality from viral hepatitis in the United States between 1999 and 2007. *Ann Intern Med* 2012; 156:271–8.
4. Ward JW. The hidden epidemic of hepatitis C virus infection in the United States: occult transmission and burden of disease. *Top Antivir Med* 2013; 21:15–9.
5. Division of Viral Hepatitis. Healthcare-associated hepatitis B and C outbreaks reported to CDC in 2008–2013. 2015. http://www.cdc.gov/hepatitis/Outbreaks/Health_careHepOutbreakTable.htm. Accessed 7 December 2015.
6. Spada E, Abbate I, Sicurezza E, et al. Molecular epidemiology of a hepatitis C virus outbreak in a hemodialysis unit in Italy. *J Med Virol* 2008; 80:261–7.

7. Spada E, Sagliocca L, Sourdis J, et al. Use of the minimum spanning tree model for molecular epidemiological investigation of a nosocomial outbreak of hepatitis C virus infection. *J Clin Microbiol* **2004**; 42:4230–6.
8. Ou CY, Ciesielski CA, Myers G, et al. Molecular epidemiology of HIV transmission in a dental practice. *Science* **1992**; 256:1165–71.
9. Esteban JI, Gomez J, Martell M, et al. Transmission of hepatitis C virus by a cardiac surgeon. *N Engl J Med* **1996**; 334:555–60.
10. Birch CJ, McCaw RF, Bulach DM, et al. Molecular analysis of human immunodeficiency virus strains associated with a case of criminal transmission of the virus. *J Infect Dis* **2000**; 182:941–4.
11. Metzker ML, Mindell DP, Liu XM, Ptak RG, Gibbs RA, Hillis DM. Molecular evidence of HIV-1 transmission in a criminal case. *Proc Natl Acad Sci U S A* **2002**; 99:14292–7.
12. Bracho MA, Gosalbes MJ, Blasco D, Moya A, Gonzalez-Candelas F. Molecular epidemiology of a hepatitis C virus outbreak in a hemodialysis unit. *J Clin Microbiol* **2005**; 43:2750–5.
13. Gonzalez-Candelas F, Bracho MA, Wrobel B, Moya A. Molecular evolution in court: analysis of a large hepatitis C virus outbreak from an evolving source. *BMC Biol* **2013**; 11:76.
14. Prosperi MC, De Luca A, Di Giambenedetto S, et al. The threshold bootstrap clustering: a new approach to find families or transmission clusters within molecular quasiespecies. *PLoS One* **2010**; 5:e13619.
15. Feray C, Bouscaillou J, Falissard B, et al. A novel method to identify routes of hepatitis C virus transmission. *PLoS One* **2014**; 9:e86098.
16. Novello S, Smith P, Chai F, et al. Hepatitis C virus transmission by a cardiac surgeon in the United States, **2015**.
17. Chai F, Xia G, Williams I, et al. Transmission of hepatitis C virus at a pain remediation clinic—San Diego, California, 2003. Presented at: 43rd Annual Meeting of the Infectious Diseases Society of America, San Francisco, California, 6–9 October 2005.
18. Lee K, Scoville S, Taylor R, et al. Outbreak of acute hepatitis C virus (HCV) infections of two different genotypes associated with an HCV-infected anesthetist. Presented at: 47th Annual Meeting of the Infectious Diseases Society of America, Philadelphia, Pennsylvania, 29 October–1 November 2009.
19. Thompson N, Novak R, White-Comstock M, et al. Patient-to-patient hepatitis C virus transmissions associated with infection control breaches in a hemodialysis unit. *J Nephrol Therapeutics* **2012**; S10:002.
20. Fischer GE, Schaefer MK, Labus BJ, et al. Hepatitis C virus infections from unsafe injection practices at an endoscopy clinic in Las Vegas, Nevada, 2007–2008. *Clin Infect Dis* **2010**; 51:267–73.
21. Moore ZS, Schaefer MK, Hoffmann KK, et al. Transmission of hepatitis C virus during myocardial perfusion imaging in an outpatient clinic. *Am J Cardiol* **2011**; 108:126–32.
22. Warner AE, Schaefer MK, Patel PR, et al. Outbreak of hepatitis C virus infection associated with narcotics diversion by an hepatitis C virus-infected surgical technician. *Am J Infect Control* **2015**; 43:53–8.
23. Bernard EJ, Azad Y, Vandamme AM, Weait M, Geretti AM. HIV forensics: pitfalls and acceptable standards in the use of phylogenetic analysis as evidence in criminal investigations of HIV transmission. *HIV Med* **2007**; 8:382–7.
24. Domingo E, Sheldon J, Perales C. Viral quasiespecies evolution. *Microbiol Mol Biol Rev* **2012**; 76:159–216.
25. Apostolou A, Bartholomew ML, Greeley R, et al. Transmission of hepatitis C virus associated with surgical procedures—New Jersey 2010 and Wisconsin 2011. *MMWR Morb Mortal Wkly Rep* **2015**; 64:165–70.
26. Ramachandran S, Xia GL, Ganova-Raeva LM, Nainan OV, Khudyakov Y. End-point limiting-dilution real-time PCR assay for evaluation of hepatitis C virus quasiespecies in serum: performance under optimal and suboptimal conditions. *J Virol Methods* **2008**; 151:217–24.
27. Dimitrova Z, Campo DS, Ramachandran S, et al. Evaluation of viral heterogeneity using next-generation sequencing, end-point limiting-dilution and mass spectrometry. *In Silico Biol* **2011**; 11:183–92.
28. Campo DS, Dimitrova Z, Yamasaki L, et al. Next-generation sequencing reveals large connected networks of intra-host HCV variants. *BMC Genomics* **2014**; 15(suppl 5):S4.
29. Forbi JC, Campo DS, Purdy MA, et al. Intra-host diversity and evolution of hepatitis C virus endemic to Cote d'Ivoire. *J Med Virol* **2014**; 86:765–71.
30. Forbi JC, Purdy MA, Campo DS, et al. Epidemic history of hepatitis C virus infection in two remote communities in Nigeria, West Africa. *J Gen Virol* **2012**; 93:1410–21.
31. Williams I. Epidemiology of hepatitis C in the United States. *Am J Med* **1999**; 107:2–9S.
32. Astrakhantseva IV, Campo DS, Araujo A, Teo CG, Khudyakov Y, Kamili S. Differences in variability of hypervariable region 1 of hepatitis C virus (HCV) between acute and chronic stages of HCV infection. *In Silico Biol* **2011**; 11:163–73.
33. Ramachandran S, Zhai X, Thai H, et al. Evaluation of intra-host variants of the entire hepatitis B virus genome. *PLoS One* **2011**; 6:e25232.
34. Skums P, Dimitrova Z, Campo DS, et al. Efficient error correction for next-generation sequencing of viral amplicons. *BMC Bioinformatics* **2012**; 13(suppl 10):S6.
35. Katoh K, Standley DM. MAFFT multiple sequence alignment software version 7: improvements in performance and usability. *Mol Biol Evol* **2013**; 30:772–80.
36. Schneider S, Roessli D, Excoffier L. ARLEQUIN, version 2000: software for population genetic data analysis. Geneva: Genetics and Biometry Laboratory, University of Geneva, **2000**.
37. Tajima F. Evolutionary relationship of DNA sequences in finite populations. *Genetics* **1983**; 105:437–60.
38. Mathworks. Natick, MA: Matlab, **2010**.
39. Kumar S, Tamura K, Nei M. MEGA3: integrated software for molecular evolutionary genetics analysis and sequence alignment. *Brief Bioinform* **2004**; 5:150–63.
40. Comaniciu D, Ramesh V, Meer P. Real-time tracking of non-rigid objects using mean shift. In: IEEE Conference in Computer Vision and Pattern Recognition. Vol 2. Hilton Head Island, SC: IEEE, **2000**:142–9.
41. Bastian M, Heymann S, Jacomy M. Gephi: an open source software for exploring and manipulating networks. Presented at: International AAAI Conference on Weblogs and Social Media, San Jose, California, 17–20 May 2009.
42. Ganova-Raeva LM, Dimitrova ZE, Campo DS, Khudyakov Y. Application of mass spectrometry to molecular surveillance of hepatitis B and C viral infections. *Antivir Ther* **2012**; 17:1477–82.
43. Olmstead A, Montoya V, Joy J, et al. Characterizing hepatitis C virus transmission dynamics using molecular phylogenetic based methods. **2015**; doi:10.1111/jvh.76_12425.
44. Poon AF, Joy JB, Woods CK, et al. The impact of clinical, demographic and risk factors on rates of HIV transmission: a population-based phylogenetic analysis in British Columbia, Canada. *J Infect Dis* **2015**; 211:926–35.
45. Skums P, Artyomenko A, Glebova O, et al. Detection of genetic relatedness between viral samples using EM-based clustering of next-generation sequencing data. Presented at: Workshop on Computational Advances in Molecular Epidemiology of the IEEE 4th International Conference on Computational Advances in Bio and Medical Sciences, Miami, Florida, 2–4 June 2014.
46. Wang G, Sherrill-Mix S, Chang K, Quince C, Bushman F. Hepatitis C virus transmission bottlenecks analyzed by deep sequencing. *J Virol* **2010**; 84:6218–28.
47. Rytasareva I, Campo D, Zheng Y, et al. Efficient detection of viral transmission with threshold-based methods. Presented at: 5th IEEE International Conference on Computational Advances in Bio and Medical Sciences, Miami, Florida, 2–4 June 2014.
48. Ramachandran S, Campo DS, Dimitrova ZE, Xia GL, Purdy MA, Khudyakov YE. Temporal variations in the hepatitis C virus intra-host population during chronic infection. *J Virol* **2011**; 85:6369–80.
49. Campo DS, Dimitrova Z, Yokosawa J, et al. Hepatitis C virus antigenic convergence. *Sci Rep* **2012**; 2:267–77.
50. Scaduto DI, Brown JM, Haaland WC, Zwickl DJ, Hillis DM, Metzker ML. Source identification in two criminal cases using phylogenetic analysis of HIV-1 DNA sequences. *Proc Natl Acad Sci U S A* **2010**; 107:21242–7.