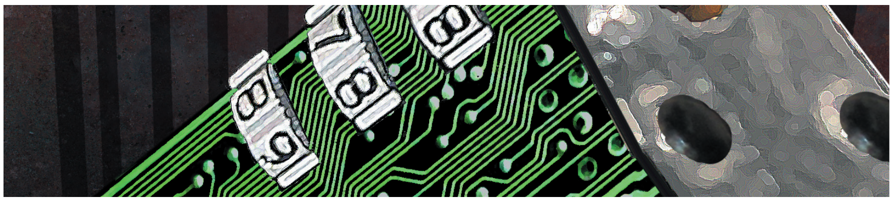
Guilty or Not Guilty: Using Clone Metrics to Determine Open Source Licensing Violations

Akito Monden and Satoshi Okahara, Nara Institute of Science and Technology, Japan

Yuki Manabe, Osaka University

Kenichi Matsumoto, Nara Institute of Science and Technology, Japan

// Programmers often unwittingly violate open source software licenses by reusing code fragments, or clones. The authors explore metrics that can reveal the existence or absence of code reuse and apply these metrics to 1,225 open source product pairs. //



TO INCREASE PRODUCTIVITY, programmers often reuse open source software (OSS) code as a part of their product. Although code reuse is generally sound practice, software companies are often unaware of how much reuse occurs, particularly if they outsource development. As more reusable OSS code becomes available online, it's becoming increasingly important for companies to inspect their software products for possible OSS code violations. This is no trivial task, since there are already myriad OSS licenses. Indeed, the violation problem is so pervasive that OSS developer-side organizations such as the Software Freedom Law Center (www.softwarefreedom.org) and gpl-violations.org have begun helping developers detect OSS license violations in commercial products.

Several services are available for OSS code detection and license identification and management. Black Duck Software's Protex analyzes source code using code print technology, comparing the source code against an OSS repository of more than 200,000 products (www.blackducksoftware.com/protex). Palamida detects reused OSS source code through multipattern searching that involves identifying matches of code fragments, or clones, and then ranking the matches according to relevance (www.palamida.com). Unfortunately, as far as we know, no one has published a performance evaluation of these services with quantifiable metrics, such as recall and precision or false-positive/negative detection rate.

We also see flaws in the core technology that these detection services use, which is to search for code clone matches between two programs and judge reuse if the programs share a large number of clones or a large enough single clone. These programs don't account for the case in which a programmer accidentally introduces clones that don't expose any licensing issue. Also, the question is still open as to what clone number or size translates to a violation. That is, what number of clones or what single clone size is the threshold for determining that the suspected program is guilty or not guilty of a licensing violation?

We decided to tackle this open problem by answering two questions:

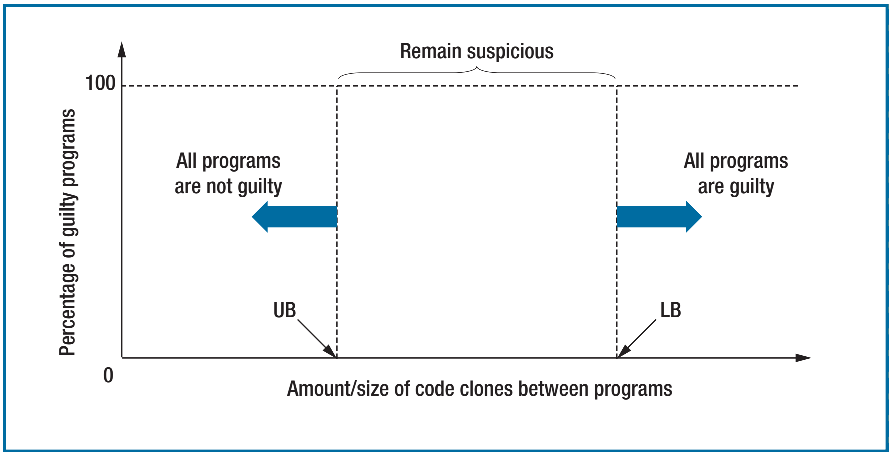
- What metrics are appropriate in evaluating the number and size of code clones between two programs?
- What's the lower bound of code

0740-7459/11/$26.00 © 2011 IEEE

clone measurement needed to conclude that the suspected program is guilty, and what is the upper bound needed to conclude that it isn't?

To answer the first question, we reviewed several potential clone metrics including ones from www.ccfinder.net, such as the ratio of similarity between another file and coverage. From these, we selected three clone-based measures: maximum length of clones (MLC), number of clone pairs (NCP), and clone-based local similarity (LSim), which looks at the percentage of duplication within a suspicious pair.

To answer the second question, we first established the framework in Figure 1 for defining guilty and not guilty and then used our metrics to determine the upper and lower bounds. To experimentally identify these bounds, we analyzed 1,225 pairs of OSS products for reuse-based clones.



Remain suspicious
100
Percentage of guilty programs
All programs are not guilty
All programs are guilty
UB
LB
0
Amount/size of code clones between programs

FIGURE 1. Defining guilty and not guilty. If two programs have a large enough number or size of code clones between them, both are considered guilty, but we need a lower bound (LB) to make this conclusion. Similarly, a program having only a small number or size of code clones is not guilty, but we need an upper bound (UB) to make this conclusion. Between these boundaries are suspicious programs, which require human inspection to determine clone reuse.

Clone Detection

In the context of our work, code clones are exact or nearly exact duplicated lines of code between a pair of source programs. These *interproduct* clones appear when one of the programs has reused the other's code or when both have reused the same piece of third-party code. We don't distinguish between these reuse conditions because companies must identify both cases to comply with software licensing.

Accidental interproduct clones are a case that must be distinguished, however, because they don't expose any licensing issues. Programmers can introduce accidental interproduct clones by using code snippets, for example, which are essentially mental macros—definitional computations that a programmer frequently codes in a regular style, such as payroll tax, queue insertion, or data structure access.[1] Fortunately, accidental clones tend to be smaller than reuse-based clones, and because size is one of our metrics, we are able to separate them.

Most existing and proposed tools[1–5] aim to detect three types of interproduct clones:[6]

- *Type 1.* An exact copy with no modifications except white space and comments.
- *Type 2.* A syntactically identical copy, with only variable, type, or function identifiers changed.
- *Type 3.* A copy with further modifications, with statements changed, added, or removed.

We're concerned only with the detection of Type 2 clones. The detection of Type 1 clones isn't sufficient for our goal because programmers often modify reused code fragments slightly to adapt them to a new environment or purpose.[6] Type 3 clone detection isn't suitable because the definition of Type 3 clones is vague, and there's no clear consensus on a suitable equivalence or similarity measure for these clones.[6]

To detect Type 2 clones, we used CCFinderX, which is a major upgrade of the CCFinder clone detector (available at www.ccfinder.net).[3] CCFinderX compares the token sequences of lines of source code and can detect code in systems up to a million lines within affordable computation time and memory requirements.

Metrics Definition

By applying MLC, NCP, and LSim, we can distinguish reuse-based clones from accidental ones. We define these metrics as

- *MLC*—number of tokens of the largest clone pair detected between two programs;
- *NCP*—sum of all clone pairs greater than 30 tokens; and
- *LSim*—percentage of duplication within the most suspicious source file pair (the one with the largest clone).

LSim is a valuable metric for detecting reuse when a programmer has copied one or more files from the other product. Given the task of inspecting programs *A* and *B*, *LSim(A,B)* is

$$LSim(A,B) = \frac{2 \times MLC(A,B)}{|a| + |b|} \times 100, \quad (1)$$

OPEN SOURCE PRODUCTS EVALUATED

We evaluated 50 products from among those listed at the Free Software Directory:

abcm2ps-3.7.20
acme-2.0.2
aide-0.9
aliens_V1.0.0
asteroids3D
avdbtools-0.3
barcode-0.98
battstat_applet-2.0.11
bc-1.06
beecrypt-4.1.2
bmi-1.3.1
calcoo-1.3.16
ccvssh-0.9.1
cdcd-0.6.6
cdparanoia-III-alpha9.8
cdrtools-2.0
cflow-1.2
check-0.8.4
chemtool-1.6.11
cinepaint-0.19-0
cvsgraph-1.5.2
cvsps-1.3.3
danpei-2.9.6
dap-3.6, Deki_Wiki_8.08.1_Kilen_Woods_source
dox-1.0beta4
easytag-1.1
electrocardiognosis
euler-1.60
fdm-1.392
ffproxy-1.6
filemanager-0.972
firestarter-1.0.3
fnord-1.9
FreeCAD-0.33
gaby-2.0.3
galculator-1.2.4
gbonds-2.0.2
gcal-3.01
geomview-1.8.1
gforge-3.0
gimp-2.3.19
glabels-2.0.3
glame-2.0.1
glom-0.9.8
gmandel-1.1.0
gmmusic-1.1.91
gnofin-0.8.4
gnubg-0.14.3
gnugo-3.6

where a and b comprise a file pair with the largest clone between A and B, $MLC(A,B)$ is the length of the largest clones, and $|a|$ and $|b|$ are the lengths of a and b as number of tokens. If a file pair a and b are identical, then LSim becomes 100 percent.

We hypothesized that the larger the value of MLC, the greater the possibility of code reuse and that the greater the value of NCP, the greater the possibility of code reuse.

Experiment Setting

To test our metrics, we selected 50 OSS products from the Free Software Directory (http://directory.fsf.org/), all of which are in C/C++, and delivered under a GNU general public license (GPL) or GNU lesser GPL (LGPL). The selected products, listed in the "Open Source Products Evaluated" sidebar, include a wide range of application domains, including security, audio, and gaming.

For these 50 products, we inspected 1,225 product pairs ($_{50}C_2$) to determine if each pair included reuse-based clones. Of the clone pairs detected, we inspected only those greater than or equal to 30 tokens, a common detection threshold for token-based clone detectors.[3] Also, as we show shortly, 30 tokens is a small enough value to identify an upper bound with which to arrive at a guilty verdict. (Although technically no pairs can violate OSS licenses because all are LGPL or GPL; for illustration, we treat them as if they *could be* guilty in terms of whether or not they contain reused code.)

Of the 1,225 pairs, 796 included one or more clones. Using the results of a two-month inspection by an expert programmer, we identified 121 product pairs of the original 796 as including reuse-based clones. We applied the following procedure to identify the 121 pairs:

- For each pair, an expert programmer (one of us) picked the largest clone and judged on the basis of his experience if it was likely to be produced accidentally. If no, the clone was considered reuse-based (guilty); if yes, it was deemed accidental (not guilty).
- If the clone was guilty, the programmer went to the next pair.
- If the clone wasn't guilty, the programmer picked the next largest clone and continued judging until clone length reached 30 tokens.

To identify the lower bound of each clone metric, for a given metric value (which we consider a *temporal* as opposed to a true lower bound), we labeled all product pairs with a greater metric value as potentially guilty. We then computed precision and recall. *Precision* is the number of correctly labeled pairs divided by the total number of pairs potentially labeled guilty. *Recall* is the number of correctly labeled products divided by the total number of pairs that are actually guilty. The lower bound is then the lowest metric value that meets 100 percent precision: no pair classified as guilty is misclassified. Similarly, to identify each metric's upper bound, we labeled all pairs with a lower metric value as belonging to not guilty and identified the largest value that meets 100 percent precision—no pair classified as not guilty is misclassified.

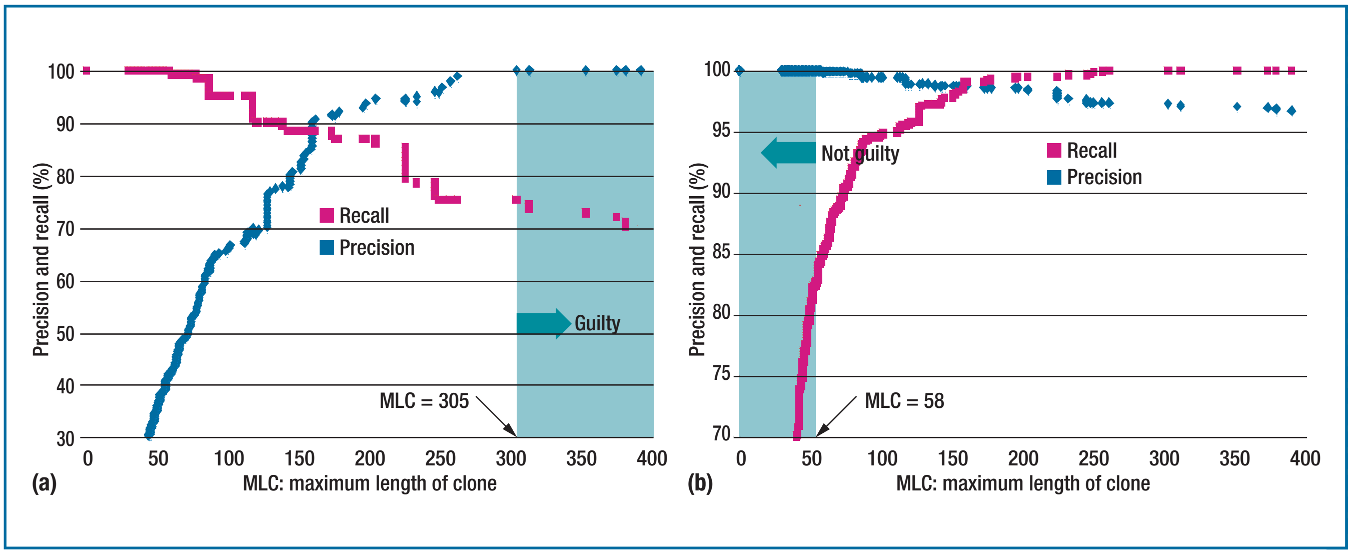


FIGURE 2. Resulting MLC values. (a) Precision and recall for identifying guilty products by MLC. We identified an MLC of 305 as the lower bound for a guilty verdict. (b) Precision and recall for identifying not guilty products by MLC. We identified an MLC of 58 as the upper bound for a not guilty verdict—that is, all pairs are not guilty if they contain clones less than or equal to 58 tokens.

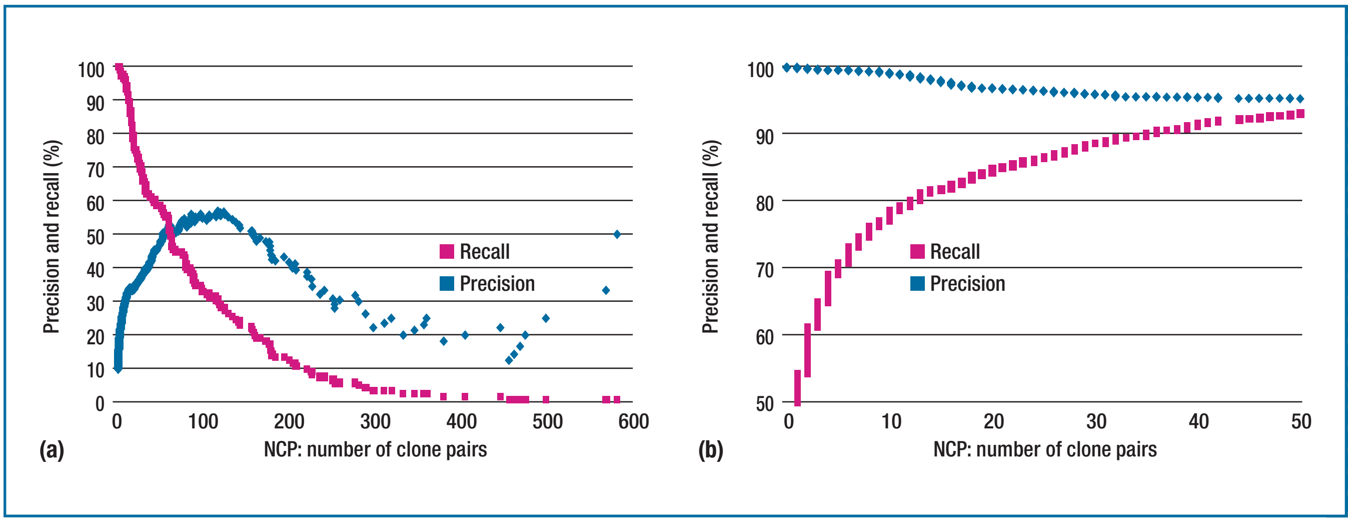


FIGURE 3. Resulting NCP values. (a) Precision and recall for identifying guilty products by NCP, and (b) precision and recall for identifying not guilty products by NCP. Because clone pairs of 30 tokens exist in all cases, there's no upper or lower bound value for distinguishing accidental and reuse-based clones.

Results

Figure 2 shows the resulting MLC values. Figure 2a shows precision and recall for identifying guilty products by MLC. We identified an MLC of 305 as the lower bound for a guilty verdict—that is, all product pairs are guilty if they contain clones greater than or equal to 305 tokens. At this point, recall is 75.2 percent, which means that relying solely on the MLC metric overlooks 24.8 percent of the guilty pairs. As Figure 2b shows, we identified an MLC of 58 as the upper bound for a not guilty verdict—that is, all pairs are not guilty if they contain clones less than or equal to 58 tokens. At this point, recall is 84.8 percent, which means 15.2 percent of the not guilty pairs are being overlooked. The rest of the product pairs—those with an MLC value of 59 to 304, which constitute 16.1 percent of all the pairs—remain suspicious, needing human inspection for a conclusive verdict.

As Figure 3 shows, we found neither an upper bound NCP nor a lower bound NCP for distinguishing accidental and reuse-based clones. Our finding implies that clone pairs of 30 tokens exist everywhere regardless of whether or not they contain reused code. This result confirmed, somewhat

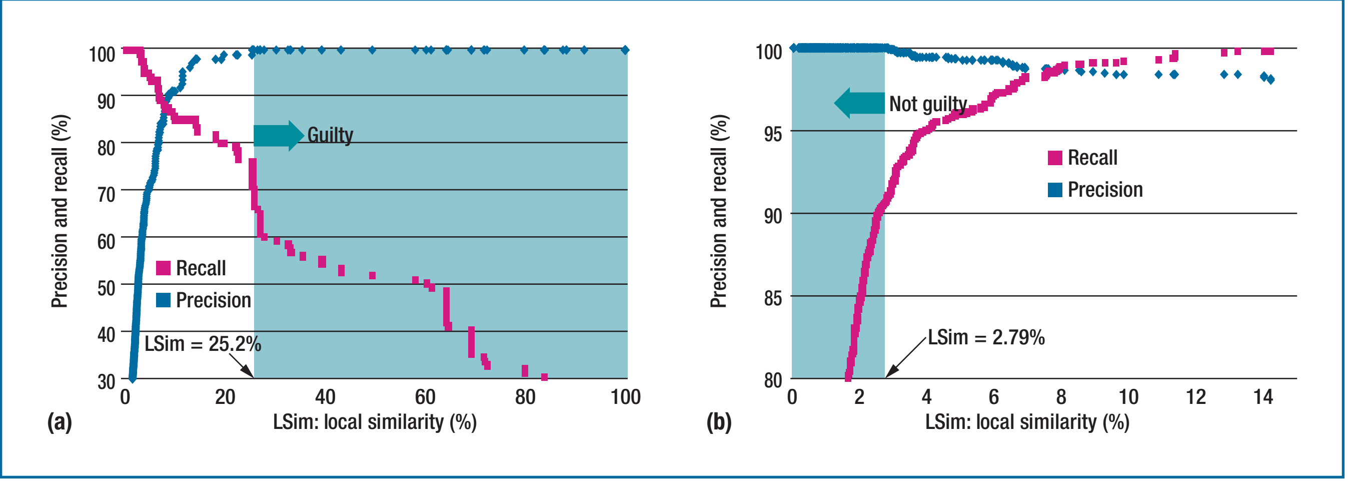


FIGURE 4. Resulting LSim values. Identification of (a) guilty and (b) not guilty product pairs. A product is guilty if its clone coverage is greater than 25.2 percent and not guilty if coverage is less than or equal to 2.79 percent.

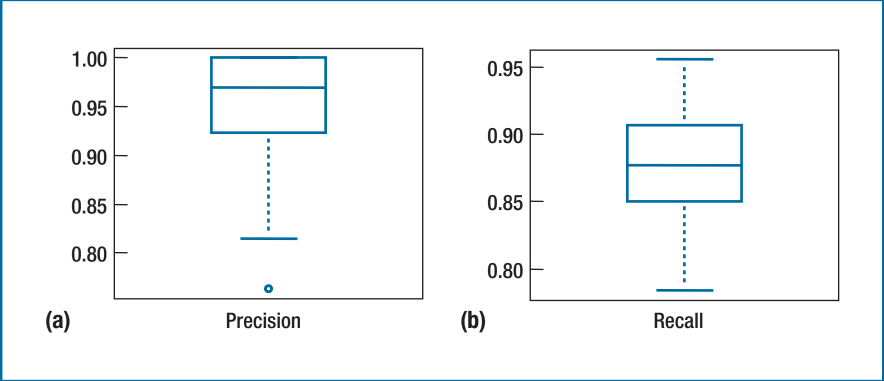


FIGURE 5. Result of logistic regression to identify guilty product pairs. (a) Precision and (b) recall.

to our surprise, that NCP is not a useful metric with which to identify reuse-based clones, although many people consider it an effective measure.

Figure 4 gives the resulting values for LSim. As Figure 4a shows, we identified a lower bound of 25.2 percent for a guilty product—that is, a pair of source files with the largest clone is guilty if its clone coverage (within a file) is greater than 25.2 percent. However, because recall is 76 percent at this point, 24 percent of the guilty pairs are being overlooked. As Figure 4b shows, we identified an upper bound of 2.79 percent for a not guilty product. At this point, recall is 91.1 percent, which means that 8.9 percent of the not guilty pairs are being overlooked. The rest of the product pairs—those with an LSim value of 2.8 to 25.1 percent, which is 10.4 percent of all pairs—remain suspicious, needing human inspection for a conclusive verdict.

These results aren't without limitations, the foremost being that we inspected only 50 OSS products. Others must take care in using our boundary values, although we believe that these values can certainly lead to the correct identification of reuse-based OSS code in most products.

Another limitation of our results is that Type 2 clones are susceptible to program-transforming attacks. Future work might use Type 3 clones or some other plagiarism-detection method such as software birthmarks,[7] which can better withstand program transformation.

Finally, our results did rely heavily on our expert programmer's initial categorization. However, we believe that the programmer has sufficient experience reading and writing a variety of software to make his judgment reliable. Moreover, for many product pairs, there is no other realistic way to distinguish reuse-based and accidentally produced clones. Such judgment is both difficult and time-consuming, and we know of no conventional study that has tried to identify the upper and lower bounds of clone metrics that can reveal guilty and not guilty products.

Classification Performance

Our results show that both MLC and LSim are effective metrics in identifying OSS code reuse. Both metrics are also effective as predictor variables to classify guilty/not guilty product pairs through a logistic regression model—a common modeling technique for two-group classification problems. To evaluate the model's classification performance, we used 100 repetitions of twofold cross validation, in which we randomly took two-thirds of the entire dataset to build a model and used the remaining third for performance evaluation.

Figure 5 shows the resulting box plots of precision and recall for identifying guilty products. The average precision was 0.955, which indicates very low (4.5 percent) misclassification of guilty products. Similarly, the average recall was 0.871, which indicates that this classification overlooked a reasonably low percentage (12.9 percent) of guilty products. In addition, the average false-positive rate (ratio of misclassified not guilty products to total not guilty products) was extremely low (0.51 percent). Thus, MLC and LSim together can result in a high precision of guilty product identification with relatively low false negative error and very low false-positive error.

We identified and experimentally tested clone-based metrics and their threshold values for distinguishing accidental and reused-based OSS code. Through this work, we were able to ascertain that MLC and LSim are the most effective clone metrics in identifying software reuse and that both MLC and LSim had both a lower-bound threshold to identify guilty products and an upper-bound threshold to identify not guilty products. NCP, on the other hand, wasn't effective in distinguishing guilty or not guilty products.

Our logistic regression model for classifying guilty products using MLC and LSim together correctly identified 95.5 percent of guilty products, while overlooking only 12.9 percent of guilty products on average. We believe that our results offer a viable alternative to existing detection services and a low-cost, relatively painless way to avoid reuse violations.

ABOUT THE AUTHORS

AKITO MONDEN is an associate professor in the Graduate School of Information Science at the Nara Institute of Science and Technology, Japan. His research interests include software protection and empirical software engineering. Monden has a DE in information science from the Nara Institute of Science and Technology. He is a member of IEEE, the ACM, the Institute of Electronics, the Information and Communication Engineers (IEICE), the Information Processing Society of Japan (IPSJ), and the Japan Society for Software Science and Technology. Contact him at akito-m@is.naist.jp.

SATOSHI OKAHARA is a systems engineer at TIS. His research interests include protection of intellectual property of software. Okahara has an ME in information science from the Nara Institute of Science and Technology, Japan. Contact him at sokahara@tis.co.jp.

YUKI MANABE is a doctoral candidate in the Graduate School of Information Science and Technology at Osaka University. His research interests include software reuse, software license protection, and software evolution. Manabe has an MS in information science and technology from Osaka University. He is a member of the ACM and the IPSJ. Contact him at y-manabe@ist.osaka-u.ac.jp.

KENICHI MATSUMOTO is a professor in the Graduate School of Information Science at Nara Institute Science and Technology, Japan. His research interests include software measurement and software process. Matsumoto has a PhD in information and computer sciences from Osaka University. He is a senior member of IEEE, and a member of the ACM, the IEICE, and the IPSJ. Contact him at matumoto@is.naist.jp.

References

1. I.D. Baxter et al., "Clone Detection Using Abstract Syntax Trees," *Proc. IEEE Int'l Conf. Software Maintenance*, IEEE CS Press, 1998, pp. 368–377.
2. B.S. Baker, "On Finding Duplication and Near-Duplication in Large Software Systems," *Proc. 2nd Working Conf. Reverse Eng.*, IEEE Press, 1995, pp. 86–95.
3. T. Kamiya, S. Kusumoto, and K. Inoue, "CCFinder: A Multi-Linguistic Token-Based Code Clone Detection System for Large Scale Source Code," *IEEE Trans. Software Eng.*, vol. 28, no. 7, 2002, pp. 654–670.
4. J. Krinke, "Identifying Similar Code with Program Dependence Graphs," *Proc. 8th Working Conf. Reverse Eng.*, IEEE Press, 2001, pp. 301–309.
5. J. Mayrand, C. Leblanc, and E.M. Merlo, "Experiment on the Automatic Detection of Function Clones in a Software System Using Metrics," *Proc. Int'l Conf. Software Maintenance*, IEEE CS Press, 1996, pp. 244–254.
6. S. Bellon et al., "Comparison and Evaluation of Clone Detection Tools," *IEEE Trans. Software Eng.*, vol. 33 no. 9, 2007, pp. 577–591.
7. H. Tamada et al., "Java Birthmarks—Detecting the Software Theft," *IEICE Trans. Information and Systems*, vol. E88-D, no. 9, 2005, pp. 2148–2158.