

# RECOMBINED FINGERPRINTS FOR PRIVACY PRESERVING IN P2P MULTIMEDIA DISTRIBUTION

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**Abstract--**Anonymous finger print has been suggested as a convenient solution for the legal distribution of multimedia contents with copyright protection whilst preserving the privacy of buyers, whose identities are only revealed in case of illegal redistribution. However, most of the existing anonymous fingerprinting protocols are impractical for two main reasons: 1) the use of complex time-consuming protocols and/or homomorphic encryption of the content, and 2) a unicast approach for distribution that does not scale for a large number of buyers. This paper stems from a previous proposal of recombined fingerprints which overcomes some of these drawbacks. However, the recombined fingerprint approach requires a complex graph search for traitor tracing, which needs the participation of other buyers, and honest proxies in its P2P distribution scenario. This paper focuses on removing these disadvantages resulting in an efficient, scalable, privacy-preserving and P2P-based fingerprinting system.

**Keywords:** P2P content distribution, anonymous fingerprinting, redistribution tracing, recombined fingerprints.

## I. INTRODUCTION

Fingerprinting digital contents [2] is an attractive option to protect the rights of content authors and owners when contents are sold or otherwise distributed over the Internet. Basically, fingerprinting consists of embedding an imperceptible mark in the distributed content (which may be audio, pictures or video) to identify the content buyer. The embedded mark is different for each buyer, but the content should stay perceptually identical for all buyers. In case of illegal redistribution, the embedded mark will allow identifying the redistributors (against whom subsequent action might be taken). Most fingerprinting schemes can be classified in three types [3]: symmetric, asymmetric and anonymous. In the first type, the merchant is the one who embeds the mark into the content; hence, the buyer cannot be formally accused of illegal redistribution, since the merchant also had access to the fingerprinted content and could be himself the redistributor. In

Asymmetric fingerprinting, the merchant does not have access to the fingerprinted copy, but he can recover the mark in case of illegal redistribution and thereby identify the malicious buyer. In anonymous fingerprinting, in addition to asymmetry, the buyer preserves her anonymity and hence she cannot be linked to the purchase of a specific content, except if she participates in an illegal redistribution. Fingerprinting schemes in the literature share the common feature of being centralized: in a way or another, the content owner/merchant has to be involved in the fingerprinting every time the content is sold to a certain buyer. Hence, distribution is basically unicast, which has the shortcoming that scalability is limited by the computing resources and bandwidth available at the content owner/merchant. This problem is further aggravated if one uses asymmetric or anonymous fingerprinting, which require more computation, communication and storage than the usual Symmetric fingerprinting. Multicast transmission of content, in which content is simultaneously transmitted to a group of receivers, is much more effective and bottleneck-free. Yet, multicast transmission does not allow sending different copies to each user, as required by fingerprinting schemes. So the question is: can we distribute fingerprinted content in a way that is more scalable than unicast transmission?

P2P distribution systems allow answering the above question in the positive. In these systems, content receivers become senders to other users. This model can be viewed as an intermediate option between unicast and multicast. P2P distribution of all kinds of contents has become popular in recent years with the bandwidth increase of home communications. Bit Torrent [5], Kademia [11] or eDonkey2000 [10] are some example P2P protocols for private file exchange. It must be noted that P2P distribution is not limited to private users in home environments; some content providers are starting to facilitate P2P download of their products (e.g. [17]). Using a P2P system allows the merchant to establish only a small number of unicast

connections with a set of  $M$  “seed” buyers who become new sources of content for other buyers. The content can eventually reach a set of  $N$  buyers with  $M \ll N$ .

#### A. Contribution and plan of this paper

We propose a P2P content distribution scheme (based on a specific P2P software) in which the merchant creates only a set of  $M$  seed copies of the content and sends them to  $M$  seed buyers. All subsequent copies are generated from the  $M$  seed copies. The copy obtained by a buyer is a combination of the copies supplied by her “parents” (sources). The fingerprint of each buyer is constructed as a binary sequence combining the sequences of her parents, in a way parallel to how DNA sequences of living beings are formed by combining the DNA sequences of their parents. The proposed scheme, which saves bandwidth and computation at the merchant, still allows tracking illegal redistributors but preserves the anonymity of honest buyers. The proposed method is thus inherently scalable compared to other systems in the literature [15], [3], [1], [7], which require (non-scalable) unicast transmissions and rely on complex CPU-intensive and/or bandwidth consuming cryptographic protocols. The cryptographic protocols used in our approach reduce to the transmission of a few encrypted hashes with low computation and communication costs. In fact, the method proposed in this paper even avoids running the embedding algorithm for non-seed buyers and thus it outperforms the abovementioned methods. The rest of this paper is organized as follows. Section II introduces DNA-inspired fingerprints, which are the foundation of the proposed scheme. Section III describes the method for P2P distribution of DNA-inspired fingerprinted contents, including the algorithm for tracing illegal redistributors. A security and privacy analysis is given in Section IV. Simulation results are reported in Section V. Section VI is a conclusion.

## II. DNA-INSPIRED FINGERPRINTS

In this section, we introduce a novel concept of automatic DNA-inspired binary fingerprints. The terms used in this paper are derived from those used in genetics to refer to DNA and heredity. The definitions of these terms in the context of this paper are introduced below.

**DNA sequence:** in nature, DNA is a molecule consisting of an ordered set of nucleotides, where each nucleotide is one of the following four (smaller) molecules: adenine, cytosine, guanine and thymine, usually represented by their initial letters (“A”, “C”, “G” and “T”). Although the DNA molecule consists of two strings, the nucleotides are always paired A-T and C-G in the two different strings, meaning that the DNA structure is redundant. The DNA molecule is a double helix string in which each string is the complementary of the other one. Hence, one of the strings contains all the information required to build the other one. In this paper, a DNA-inspired fingerprint is constructed as a binary sequence and each bit

can be considered as the counterpart of the nucleotides in real DNA sequences. Although each of the real DNA sequences’ nucleotides can be thought of as a two-bit symbol (since there are four different nucleotides), the analogy can still be established using 1bit nucleotides. This is similar to what is done in genetic algorithms [9]. **Gene:** a segment of the DNA sequence which encodes a given protein –and thus has some impact in heredity and in the biological chemistry of the living being– is called a gene. Similarly, a segment of the DNA-inspired fingerprint sequence is called a “gene” in this paper. Although real life genes have different sizes, the sizes of the genes in this paper are taken to be equal for simplicity and without loss of generality (variable sized genes might be used with no additional complexity in the proposed system). In addition, in nature, not all segments of the DNA sequence encode genes. Nevertheless, in this paper, all “nucleotides” (bits) do belong to one of the genes of the DNA-inspired fingerprint.

**Mating and heredity:** in nature, the genes of an offspring are basically a combination of the genes of its parents (although some other processes such as mutation and crossover may produce fragments of DNA which are different in the offspring with respect to both its parents). Similarly, in this paper, when a buyer obtains a copy of a P2P-distributed content using some specific software, the DNA-inspired fingerprint of her copy will be a combination of the genes of the sources of the content (referred to as “parents” from the biological analogy). In this case, the number of parents for a buyer does not have to be exactly two as in the natural world. Hence, the mating process in the suggested fingerprinting scenario must be understood in a generalized sense, not limited to two parents. In this proposal, fingerprints can be considered as being “automatically generated” from the fingerprints of the parents. Despite this “automatic generation” of fingerprints, the constructed sequences are still valid for identification purposes, just like DNA traces can be used in criminal investigations to identify the suspect of an offence. **Mutation and crossover:** different types of changes may occur in DNA molecules resulting in the modification of some of the nucleotides in the sequence. These changes may affect a single nucleotide or a full segment of the DNA sequence. Basically, crossover occurs when the two complementary DNA strings are recombined during DNA replication and mutation refers to different random-like errors during DNA replication. Mutation and crossover provide mechanisms which allow the DNA sequence of an offspring to include genes which are different from those of its parents. If it is allowed that a buyer can obtain her copy of the contents from only one parent (source), mutation (and/or crossover) shall be used to produce a different version of the fingerprint, as required in fingerprinting applications (since two different buyers must have different fingerprints). Note that, although the DNA-inspired fingerprints are defined as a single bitstream, it is still possible to consider that a complementary sequence exists by using its negation. Crossovers can thus be simulated between a binary fingerprint and its negation.



different for different buyers is to enforce at least two parents for each buyers, and this is the solution adopted in this paper.

#### B. The P2P distribution protocol

To bootstrap the system, a few copies of the content with different fingerprints must be produced. The merchant can produce a small number  $M$  of instances of the content and embed different pseudo-random binary sequences (DNA-inspired fingerprints) into them. These copies are then transferred to the  $M$  seed buyers who may be genuine buyers of the content or dummy buyers created by the merchant to facilitate the distribution. In either case, the seed buyers will be contacted by second-generation buyers to download further copies of the content. The association of the first  $M$  fingerprints with the pseudonyms of the first  $M$  buyers must be recorded either by the merchant or some trusted authority.

Once the system is bootstrapped, all further transactions occur without any need to run the embedding algorithm as far as at least two parents are chosen for each buyer (as discussed above). Note also that all fingerprints from buyer  $M + 1$  to the final one ( $N$ ) will remain completely anonymous (only known by the buyers themselves) and cannot be related to real identities. Thus, anonymous fingerprinting is obtained in a much simpler way than with any of the existing proposals in the literature [15], [3], [1], [7], which require running complex cryptographic protocols for every transaction. As detailed below, in our proposal only the transaction monitor keeps a record of the transactions between buyers in case they are required in future DNA relationship tests. In any case, real identities are not known by the transaction monitor and, hence, privacy is fully preserved.

The P2P distribution protocol is summarized below.

##### *Protocol 1 (P2P distribution):*

- 1) For  $i := 1$  to  $M$ , the merchant generates the  $i$ -th pseudo-random binary fingerprint and embeds it into the original content to produce the first  $M$  fingerprinted files. These  $M$  fingerprints must have low pairwise correlations.
- 2) For  $i := 1$  to  $M$ , the merchant forwards the  $i$ -th seed copy to the  $i$ -th seed buyer. If the seed buyers are genuine rather than dummy buyers, this step can be anonymized using cryptographic protocols.
- 3) For  $i := M + 1$  to  $N$ , the  $i$ -th buyer obtains her copy of the content by joining fragments obtained from a set  $S_i$  of parent nodes (sources) such that  $S_i \subseteq \{B_1, \dots, B_{i-1}\}$  and  $|S_i| > 1$ , where  $|\cdot|$  is the cardinality operator and  $B_j$  refers to the  $j$ -th buyer. This transaction is performed via a proxy (or a set of proxies) and with an anonymous protocol such as [4].

The proxy registers each transaction at the transaction monitor. When all the fragments have been transferred for a

buyer, the whole fingerprint's hash is also stored in the transaction monitor.

The hash of the fingerprint is stored as a ciphertext in the transaction monitor: it is encrypted using the public key of the transaction monitor and the public key of each parent. There will be as many records for each buyer as parents she has, and the fingerprint's hash is stored encrypted with the parent's public key and the transaction monitor's public key. In this way, in case of a traitor tracing investigation, the transaction monitor will need the cooperation of at least one parent to decrypt the hash. This provides additional anonymity and protection to buyers.

#### C. The traitor tracing protocol

We now show that the proposed fingerprinting method allows identification of illegal redistributors (traitors) of fingerprinted contents. Assuming that the embedding scheme is secure and robust enough so that malicious users cannot easily erase their fingerprints without making the content unusable (this is the standard marking assumption, [2]), the following method can be used by a tracing authority to identify the source of an illegally distributed copy.

##### *Protocol 2 (Traitor tracing):*

- 1) The fingerprint  $f$  of the illegally distributed content  $X_f$  is extracted using the extraction method.
- 2) The initial test set  $T_0$  is built with the  $M$  buyers of the seed versions of the file.
- 3) Let  $i := 0$ .
- 4) The tracing authority contacts the buyers in the current set  $T_i$  and retrieves the hashes of their fingerprints from the transaction monitor. This step requires the private key of one parent of these buyers (the merchant in case  $i = 0$  and the selected ancestor in the set  $T_{i-1}$  otherwise) and the private key of the transaction monitor. Then, the fingerprints of the buyers of  $T_i$  are extracted from their copies of the content and the hash function  $h$  is applied to each segment to obtain the fingerprints' hashes. If any of the buyers' fingerprints produces a hash which does not match the corresponding record in the transaction monitor, the associated buyer is accused of forgery (contract breach).



5) If no forgery has been detected in the previous step, the DNA relationship test is carried out with the fingerprints of the buyers in the current set  $T_i$ . This step is conducted as a simple bitstream correlation. Given the fingerprint  $f$  to be traced and the test fingerprint  $f'$  extracted from the copy  $X_{f'}$  corresponding to a buyer in  $T_i$ , both fingerprints with length  $L$ , the correlation  $C(f, f')$  between  $f$  and  $f'$  is computed as follows:

$$C(f, f') = \frac{1}{L} \sum_{j=1}^L (-1)^{f_j \oplus f'_j}, \quad (1)$$

where  $f_j$  and  $f'_j$  are, respectively, the  $j$ -th bits of  $f$  and  $f'$ , and  $\oplus$  refers to the exclusive-or operation. In case

of forgery, this step can be computed with the hashes of the fingerprints instead of the fingerprints themselves. If the correlation of the hashes is one, the corresponding buyer is charged of illegal redistribution and the traitor tracing protocol halts.

A guilty redistributor may try to randomly alter  $X_{f'}$ , but this would make the content unusable according to the marking assumption [2]. In addition, such an alteration would be detected as a hash mismatch. If a buyer is afraid of being framed by the authority, she might prefer not to reveal  $X_{f'}$ ; in this case, buyer and tracing authority may engage in a secure multiparty computation to compute Expression (1).

6) If no culprit has been identified so far, there may be three outcomes of the previous step:

- a) One or more buyers in  $T_i$  refuse to collaborate with the tracing authority in computing their correlations with  $f$ . In such a case, depending on the correlation between the hash  $h_f$  and the hash(es) of the refusing buyer(s) (recorded in the transaction monitor), the refusing buyer(s) is(are) accused either of redistribution (if hashes are identical) or contract breach (otherwise). If the correlation between hashes is less than 1, this correlation can be used as a replacement for the correlation between the fingerprints.
- b) One buyer in  $T_i$  has  $C(f, f') = 1$ ; in this case, this buyer is identified as the culprit.

c) Otherwise, the buyer in  $T_i$  who has the maximum correlation with  $f$  is taken as the most likely ancestor of the buyer of the illegally distributed copy and a new set  $T_{i+1}$  of buyers is built with all the children of this ancestor buyer, excluding any children buyers who have been already analyzed (remember that each buyer will have several parents). These children can be obtained from the transaction records of the transaction monitor. Once the new set  $T_{i+1}$  is available, set  $i := i + 1$  and go to Step 4.

The maximum correlation criterion will work with a high probability, but a higher correlation might accidentally be obtained for a non-ancestor of the buyer of the illegally distributed copy. For example, a descendant D of the illegal redistributor I may have, as another ancestor A, a node of the graph which is also an ancestor of I. This would produce a high correlation but the chain from A to D skips the illegal redistributor I. In this situation, backtracking is required in the tracing algorithm described above. A complete subnetwork should be exhausted until all nodes of the subgraph having no children are considered. When a complete subnetwork is exhausted, the element of T with the second maximum correlation would be chosen as the candidate ancestor of the traitor to be identified. When all elements of T I have been considered without success (i.e. without being able to accuse anyone), the procedure would backtrack to the set T I fil

Backtracking has been needed in a very small number of the simulations presented in Section V.

We now give some examples of the operation of Algorithm 2. Figure 2a shows an example of a subgraph of the P2P distribution network. This can be modeled as a directed graph from content sources (parents) to content destinations (children). The figure illustrates how Algorithm 2 discovers that the fingerprint in the content (traced fingerprint) is the one of buyer  $B_{53}$ . The system begins testing the DNA relationship between this traced fingerprint and a set  $T$  formed by all the children of the merchant. If  $M = 10$ , then  $T_0 = \{B_1, B_2, \dots, B_{10}\}$ . In this case, three buyers among those in  $T_0$ , namely  $B_3$ ,  $B_6$  and  $B_8$ , have DNA-inspired fingerprints with the top three correlations with the traced fingerprint (no wonder if one knows that  $B_{53}$  is the traced buyer, because  $B_3$ ,  $B_6$  and  $B_8$  are ancestors of  $B_{53}$ ). It turns out that  $B_3$  is the one with the highest correlation (again, no surprise if one knows that  $B_{53}$  is the traced buyer;  $B_3$  and  $B_6$  are the most likely to have fingerprints with the highest correlation with  $B_{53}$ , since two of the parents of  $B_{53}$  are children of  $B_3$  and  $B_6$  is also a parent of  $B_{53}$ ). The next iteration is performed with all the children of  $B_3$ , namely  $T_1 = \{B_{12}, B_{15}, B_{23}\}$ .

The DNA relationship yields the highest correlation with B (if one knows that B 53 1 = fB 12 is the traced buyer, since B has four parents including B 12 and B , the correlation of the fingerprints of the latter two buyers with the fingerprint of B must be around 0.25). Now, the set T 15 is formed with buyer

B 15 's children: T 2 = fB 25 ; B 53 ; B 65 2 g. In this situation, B 53 ; B 72 will be found to have a fingerprint with correlation 1 with the traced fingerprint unless she refuses to take the DNA relationship test. In any case, she will be accused of illegal redistribution because of the perfect match between her fingerprint's hash and the traced one. In Figure 2a, the nodes highlighted in grey are the ones yielding the highest correlations and rectangles are used to enclose the nodes that are involved in DNA relationship tests.

Figure 2b shows an example of a situation which requires backtracking, where B is the traitor. The curved dotted arrow in the figure does not represent an edge of the graph, but the backtracking process. In this situation, the set T 48 = fB g is formed as in the previous example and the maximum correlation is obtained for B 1 ; B 2 ; : : : B 10 . Note that this is an ancestor of B 48 4 (as expected) but it shares a common child (B) with the traitor. The new set of candidates is constructed with B 51 4 's children as T g. In this case, B 51 1 = fB 13 ; B 17 ; B 24 ; B 51 is very likely to produce maximum correlation with the traced fingerprint (the one of B 48 ), because B is a parent of B 51 and the other parent (B 48 ) is an ancestor of B . Once B is selected, her children (if any) and all her descendance subgraph would be examined without finding a correlation C = 1. Finally, after analyzing all the descendance subgraph, backtracking occurs, going back to the set T 51 and picking the second highest correlation in the set, which is found for B 1 , who is a true ancestor of the traitor (B ). After that, two more iterations are required to find the illegal redistributor (descendants of B 17 and descendants of B 48 22)

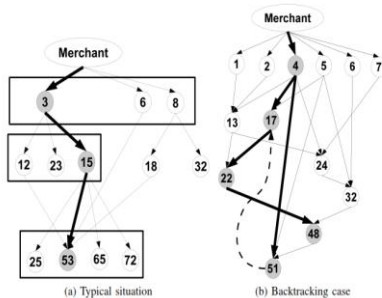


Fig. 2: Traitor tracing examples for the P2P content distribution scheme (typical situation and backtracking case)

#### IV. SECURITY AND PRIVACY ANALYSIS

This section analyzes the security and privacy properties for the proposed system: the security assumptions (including buyer frame proofness) are summarized and a collusion resistant version of the scheme is discussed. A. Security assumptions The security assumptions of the proposed system are the following:

1) The proxies and the transaction monitor do not know real identities, only pseudonyms. Hence, neither the proxies nor the transaction monitor can break the privacy of buyers by themselves. A specific purchase by a buyer can only be leaked by a coalition of the merchant and at least one of the proxies

or the transaction monitor. The merchant is the only party having access to the real identities.

2) The only threat to buyer security (resulting in an innocent buyer being framed) is a coalition of all proxies chosen by a buyer. Proxies have access to the cleartext of the content's fragments and they have to share the fragments of the child buyers' fingerprint hash. This means that proxies need to have contact between them during the process. If all the proxies chosen by a buyer collude, they can replicate the content transferred to the buyer by joining the different pieces together. Thus, they can redistribute the content illegally to frame an innocent buyer. This paper assumes that proxies are honest.

3) The traitor tracing protocol requires that at least one of the parents of a buyer provide her secret key to obtain the fingerprint's hash stored at the transaction monitor. If a buyer refuses to co-operate by providing her fingerprint's correlation with the traced fingerprint, at least one of the parents of the buyer must co-operate to decrypt her child's fingerprint hash. If all the parents of a non cooperative child refused to do so, the system would not be able to trace the child if she were the traitor. However, cheating parents would have to pay some punishment (fine) due to contract breach, and they are unlikely to incur such a risk to favor an unknown child.

4) Parents are also expected to provide the fingerprint's hash bit of each fragment. A simple solution to avoid cheating about it consists in having the fingerprint's hash bits and fragments signed at the origin by the merchant. The signature could thus be verified by the proxies (who are assumed honest).

5) As already discussed, the merchant has access to the seed buyers' fingerprints and, hence, if they are genuine buyers, they can be accused if the merchant behaved maliciously and redistributed their copy of the content. To avert such a dishonest behavior, the simplest alternative is for the M seed buyers not to be real buyers, but dummy buyers created by the merchant to bootstrap the P2P distribution protocol. Hence, the first real buyer would be the M + 1-th one.

#### B. Collusion resistance

Fingerprinting schemes are not only required to trace authentic fingerprints, but also forged instances created by advanced attackers. When several buyers collude, they create a new copy of the content whose fingerprint is formed by a mixture of the bits of the fingerprints of the colluders (standard marking assumption) and, thus, a new forged fingerprint results. In this section, we show how the existing anti-collusion fingerprinting codes (e.g. [2], [8], [16], [14]) can be used also in the proposed DNA-inspired fingerprinting system. This means that the suggested scheme can be made as resistant against collusion as any of the existing anti-collusion techniques of the literature.

The following method is suggested to endow the DNA inspired fingerprinting system with collusion resistance:

Each gene shall be encoded with a (gene-level) anti-TABLE I: Average number and percentage of DNA relationship tests on non-seed buyers in an exponentially growing population

Gener.	Popul.	Average DNA tests		Backtrack. (100 sim.)
		1 simul.	100 simul.	
$k = 2$	$N = 20$	3.40 (34.0%)	3.71 (37.1%)	0%
$k = 3$	$N = 40$	6.93 (23.1%)	7.29 (24.3%)	0%
$k = 4$	$N = 80$	12.26 (17.5%)	11.69 (16.7%)	0.6%
$k = 5$	$N = 160$	18.99 (12.7%)	17.05 (11.4%)	1.2%
$k = 6$	$N = 320$	24.31 (7.8%)	23.76 (7.7%)	2.7%

collusion code which can be used to reconstruct the gene of one of the colluders. Since the merchant embeds the fingerprint of the seed buyers, an honest merchant suffices to guarantee that all the genes are encoded using this specific codebook. Hence, if a set of colluders fabricate a copy of the content and redistribute it, each gene may be decoded to recover the corresponding gene of one of the colluders.

□ The fingerprints must be constructed in such a way that their hashes are also code words of a (hash-level) collusion-resistant code. In this way, after a collusion, when the genes have already been reconstructed by the tracing authority, the hash of at least one of the colluders will be obtained. In this case, cooperation by the proxies is required to construct a valid codeword for each hash. For example, if using an error-correcting code as an anti-collusion code (e.g. [8]) and assuming the code is in systematic form, the “data” bits of the hash can be chosen randomly, whereas specific parents having the required hash bit shall be selected for the redundancy bits of the hash. The proxy can contact potential parents subsequently, requiring a specific hash bit for a given gene, and only the ones having the specific hash bit for that gene would be accepted as the source for that specific fragment of the content. In this case, the traitor tracing algorithm will stop when a correlation equal to one is found with respect to the fingerprint’s hash instead of the whole fingerprint, since only the hash will be perfectly reconstructed in case of collusion.

## V. SIMULATION RESULTS

This section presents a set of simulated experiments to illustrate the properties of the proposed system. In particular, we focus on the number of buyers which will be required to cooperate with the tracing authority in case of a traitor tracing investigation. All simulations presented below use DNA-inspired fingerprints formed by 4096 bits, divided into 128 genes of 32 bits each. A more detailed analysis and empirical results on the method proposed in this paper, including examples which are closer to real-world scenarios, can be found in [12].

The first simulation consists of producing different generations of buyers using an exponential growth approach and checking the average number of required DNA relationship tests. The following assumptions are made:

- 1) The first generation is formed by  $M = 10$  seed buyers.
- 2) At each generation, the population increases by 100%. This means that, on average, each buyer sends the whole content allowing feed a new buyer (a new copy of the entire content). Hence, the second generation would be formed by  $M$  new buyers. The third generation would be formed by  $2M$  buyers, and so on. With this assumption, the population increases exponentially after each generation. For example, after six generations, the population would be  $M + M + 2M + 4M + 8M + 16M = 32M$ .

If  $k$  is the number of generations, the total population is  $N = 2^{k-1}M$ .

- 3) For each buyer, between two and four parents are chosen  $k1$  at random from the previous generations. Hence, the average number of parents per non-seed nodes is three. After simulation, the results shown in Table I have been obtained. The results show a single simulation and the average of 100 simulations with 100 different seeds in the pseudorandom number generator in order to reduce the bias of the results. It can be seen that no significant differences appear between 1 and 100 simulations. The last column represents the average percentage of buyers requiring backtracking in the 100 simulations. Not surprisingly, as the network (graph) becomes larger, more buyers will require backtracking, but the percentage is always small. In any case, the fraction of non-seed buyers affected by one DNA relationship test decreases to zero as the number of generations grows: the more buyers involved, the higher the probability of remaining anonymous in one DNA relationship test.

It may appear that the decrease in the percentage of buyers involved in DNA relationship tests in the course of an investigation decreases to zero because of the exponential increase in population occurring at each generation. However, this is not the case. The decrease of this ratio of tested buyers depends on the population and not on the particular way it grows. To illustrate this behavior, the following simulations have been performed with a population growing linearly at each generation:

- 1) The first generation is, again, formed by the  $M = 10$  seed buyers who obtain their fingerprinted contents from the merchant.
- 2) At each new generation,  $M = 10$  new buyers obtain their contents from a variable number of parents between two and four (and thus, the average number of parents is, again, three). Again, parents are chosen at random from the previous generations.
- 3) With this scenario, the population  $N$  increases linearly with the number of generations: there are  $N = kM$  buyers after the  $k$ -th generation. We present simulation results comparing the



linear and exponential growths scenarios for the same population. The results are shown in Table II and Figure 3. It can be observed that, when populations are of the same size, the results are almost identical irrespective of the number of generations and the growth model. In these tests, the seeds of the pseudo-

TABLE II: Average number and percentage of DNA relationship tests on non-seed buyers: comparison between exponential and linear growth for the same population

Population	Exponential growth		Linear growth	
	Gener.	Average tests (100 simul.)	Gener.	Average tests (100 simul.)
$N = 20$	$k = 2$	3.71 (37.1%)	$k = 2$	3.71 (37.1%)
$N = 40$	$k = 3$	7.29 (24.3%)	$k = 4$	6.90 (23.0%)
$N = 80$	$k = 4$	11.69 (16.7%)	$k = 8$	10.62 (15.2%)
$N = 160$	$k = 5$	17.05 (11.4%)	$k = 16$	15.43 (10.3%)
$N = 320$	$k = 6$	23.76 (7.7%)	$k = 32$	22.23 (7.2%)

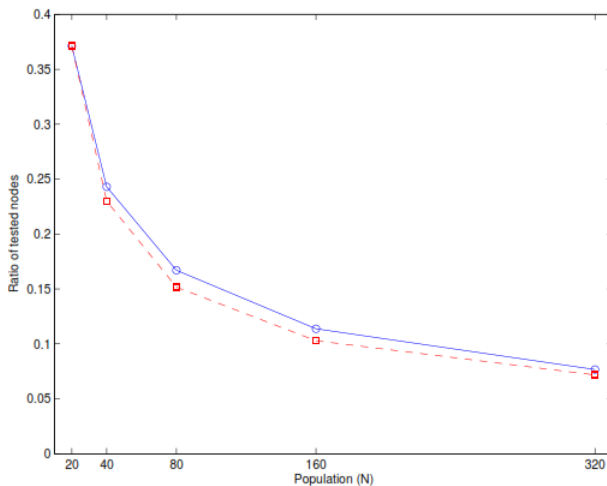


Fig. 3: Average fraction of non-seed buyers affected by DNA relationship tests: comparison between exponential growth (circle, solid) vs. linear growth (square, dashed) for the same population. Abscissae is population size random number generator have been adjusted such that the results for two generations ( $N = 20$ ) are the same with both growth models.

## VI. CONCLUSION

A DNA-inspired fingerprinting scheme designed for P2P content distribution is presented. The proposed scheme allows the merchant to trace traitors who redistribute the content illegally. The merchant knows at most the fingerprinted copies of the seed buyers, but not the fingerprinted copies of non-seed buyers (the vast majority). Hence, the merchant does not know the identities of non-seed buyers. Whenever a traitor needs to

be traced, only a small fraction of honest users must cooperate by providing their fingerprinted copies (quasi-privacy).

Collusion resistance against dishonest buyers trying to create a forged copy without any of their fingerprints is also discussed. Finally, buyer frameproofness is guaranteed since a malicious merchant does not have access to the fingerprinted copies of non-seed nodes. Thus, he will not be able to frame an honest buyer since random guess is not an option to construct a valid fingerprint (due to combinatorial explosion). Future research will involve designing backtrack-free protocols for traitor tracing in such a way that the fraction of honest buyers who must co-operate in case of an illegal redistribution is reduced. The security analysis of the proposed scheme against malicious proxies, who may even collude with other parties is also left for the future research.

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