# Almost k-wise Independent Sample Spaces and Their Cryptologic Applications

Kaoru Kurosawa<sup>1</sup>, Thomas Johansson<sup>2</sup>, Douglas Stinson<sup>3</sup>

 <sup>1</sup> Dept. of Computer Science
 Graduate School of Information Science and Engineering Tokyo Institute of Technology
 2-12-1 O-okayama, Meguro-ku, Tokyo 152, Japan kurosawa@ss.titech.ac.jp

<sup>2</sup> Dept. of Information Technology, Lund University, PO Box 118, S-22100 Lund, Sweden thomas@it.lth.se

<sup>3</sup> Dept. of Computer Science and Engineering University of Nebraska Lincoln NE 68588, USA stinson@bibd.unl.edu

Abstract. An almost k-wise independent sample space is a small subset of m bit sequences in which any k bits are "almost independent". We show that this idea has close relationships with useful cryptologic notions such as multiple authentication codes (multiple A-codes), almost strongly universal hash families and almost k-resilient functions.

We use almost k-wise independent sample spaces to construct new efficient multiple A-codes such that the number of key bits grows linearly as a function of k (here k is the number of messages to be authenticated with a single key). This improves on the construction of Atici and Stinson [2], in which the number of key bits is  $\Omega(k^2)$ .

We also introduce the concept of  $\epsilon$ -almost k-resilient functions and give a construction that has parameters superior to k-resilient functions.

Finally, new bounds (necessary conditions) are derived for almost k-wise independent sample spaces, multiple A-codes and balanced  $\epsilon$ -almost k-resilient functions.

# 1 Introduction

An almost k-wise independent sample space is a probability space on m-bit sequences such that any k bits are almost independent. A  $\epsilon$ -biased sample space is a space in which any (boolean) linear combination of the m bits has the value 1 with probability close to 1/2. These notions were introduced by Naor and Naor [17] and further studied in [1] due to their applications to algorithms and complexity theory. However, there are also cryptographic applications: Krawczyk applied  $\epsilon$ -biased sample spaces to the construction of authentication codes [13].

In this paper, we investigate several new relationships between almost k-wise independent sample spaces and useful cryptologic notions such as multiple

authentication codes (multiple A-codes) [2] and k-resilient functions [10, 3, 11, 24, 4].

In a multiple A-code,  $k \ge 2$  messages are authenticated with the same key. (In "usual" A-codes, just one message is authenticated with a given key.) Recently, Atici and Stinson [2] defined some new classes of almost strongly universal hash families which allowed the construction of multiple A-codes. Here, we prove that almost k-wise independent sample spaces are equivalent to multiple A-codes. This allows us to obtain a more efficient construction of multiple A-codes from the almost k-wise independent sample spaces of [1].

Next, we present a lower bound on the size of the keyspace in a multiple A-code. Numerical examples show that the multiple A-codes we construct are quite close to this bound. Further, from the above equivalence, a lower bound on the size of almost k-wise independent sample spaces is obtained for free. (While a lower bound on the size of  $\epsilon$ -biased sample spaces was given in [1], no lower bound was known for the size of almost k-wise independent sample spaces.)

Finally, we generalize the idea of resilient functions. A function  $\phi: \{0, 1\}^m \rightarrow \{0, 1\}^l$  is called *k*-resilient if every possible output *l*-tuple is equally likely to occur when the values of *k* arbitrary inputs are fixed by an opponent and the remaining m - k input bits are chosen at random. This is a useful tool for achieving key renewal: an *m*-bit secret key  $(x_1, \dots, x_m)$  can be renewed to a new *l*-bit secret key  $\phi(x_1, \dots, x_m)$  about which an opponent has no information if the opponent knows at most *k* bits of  $(x_1, \dots, x_m)$ .

We show that k can be made larger if the definition of resilient function is slightly relaxed. Thus, we define an  $\epsilon$ -almost k-resilient function as a function  $\phi$  such that every possible output *l*-tuple is almost equally likely to occur when the values of k arbitrary inputs are fixed by an opponent. (The statistical difference between the output distribution of a k-resilient function and an  $\epsilon$ -almost k-resilient function is  $\epsilon$ .) We prove that a large set of almost k-wise independent sample spaces is equivalent to a balanced  $\epsilon$ -almost k-resilient function, generalizing a result of [24]. From this equivalence, we are able to obtain both efficient constructions and bounds for balanced  $\epsilon$ -almost k-resilient functions.

# 2 Almost k-wise independent sample spaces

Let  $S_m \subseteq \{0,1\}^m$ , and let  $X = x_1 \cdots x_m$  be chosen uniformly from  $S_m$ .

**Definition 1.** [1] We say that  $S_m$  is an  $(\epsilon, k)$ -independent sample space if for any k positions  $i_1 < i_2 < \cdots < i_k$  and any k-bit string  $\alpha$ , we have

$$|\Pr[x_{i_1}x_{i_2}\cdots x_{i_k}=\alpha] - 2^{-k}| \le \epsilon.$$
(1)

If  $\epsilon = 0$ , then  $S_m$  is equivalent to an orthogonal array  $OA_{\lambda}(k, m, 2)$ , where  $\lambda = |S_m|/2^k$ .

The following efficient construction for  $(\epsilon, k)$ -independent sample spaces is proved in [1].

**Proposition 2.** There exists an  $(\epsilon, k)$ -independent sample space  $S_m$  such that

$$\log_2 |S_m| = 2(\log_2 \log_2 m - \log_2 \epsilon + \log_2 k - 1).$$

In this section, we prove that almost k-wise independent sample spaces are equivalent to multiple authentication codes (more precisely, almost strongly universal-k hash families, as defined in [2]). This allows us to obtain more efficient multiple A-codes than were previously known.

#### 2.1 Multiple A-codes and ASU-k hash families

We briefly review basic concepts of (multiple) authentication codes. In the usual Simmons model of authentication codes (A-codes) [21, 22], there are three participants, a transmitter, a receiver and an opponent. In an A-code without secrecy, the transmitter sends a message (s, a) to the receiver, where s is a source state (plaintext) and a is an authenticator. The authenticator is computed as a = e(s), where e is a secret key shared between the transmitter and the receiver. The key e is chosen according to a specified probability distribution.

In a multiple A-code, we suppose that an opponent observes  $i \ge 2$  messages which are sent using the same key. Then the opponent places a new bogus message (s', a') into the channel, where s' is distinct from the *i* source states already sent. This attack is called a *spoofing attack of order i*.  $P_{d_i}$  denotes the success probability of a spoofing attack of order *i*, see [15].

Almost strongly universal hash families are a very useful way of constructing practical A-codes. This idea was introduced by Wegman and Carter [26], and further developed and refined in papers such as [23, 5, 13, 12]. Atici and Stinson [2] generalized the definitions so that they could be applied to multiple A-codes. We review these definitions now.

**Definition 3.** An (N; m, n) hash family is a set F of N functions such that  $f: A \to B$  for each  $f \in F$ , where |A| = m, |B| = n and m > n.

**Definition 4.** An (N; m, n) hash family F of functions from A to B is  $\epsilon$  almost strongly universal-k (or  $\epsilon$ -ASU (N; m, n, k)) provided that, for all distinct elements  $x_1, x_2, \dots, x_k \in A$ , and for all (not necessary distinct)  $y_1, y_2, \dots, y_k \in B$ , we have

$$|\{f \in F : f(x_i) = y_i, 1 \le i \le k\}| \le \epsilon \times |\{f \in F : f(x_i) = y_i, 1 \le i \le k-1\}|.$$

The following result gives the connection between  $\epsilon$ -ASU (N; m, n, k) hash families and multiple A-codes.

**Proposition 5.** [2] There exists an A-code without secrecy for m source states, having n authenticators and N equiprobable authentication rules and such that  $P_{d_{k-1}} \leq \epsilon$ , if and only if there exists an  $\epsilon$ -ASU (N; m, n, k) hash family F.

#### 2.2 Equivalence of hash families and sample spaces

We can can rephrase Definition 1 in terms of hash families, and generalize it to the non-binary case, as follows.

**Definition 6.** An (N; m, n) hash family F of functions from A to B is  $(\epsilon, k)$ -*independent* if for all distinct elements  $x_1, x_2, \dots, x_k \in A$ , and for all (not necessary distinct)  $y_1, y_2, \dots, y_k \in B$ , we have

$$|\Pr(f(x_i) = y_i, 1 \le i \le k) - n^{-k}| \le \epsilon,$$
(2)

where  $f \in F$  is chosen uniformly at random.

The following results are straightforward.

**Proposition 7.** An  $(\epsilon, k)$ -independent sample space  $S_m$  is equivalent to an  $(\epsilon, k)$ independent  $(|S_m|; m, 2)$  hash family.

**Proposition 8.** If there exists an  $(\epsilon, k)$ -independent sample space  $S_m$ , then there exists an  $(\epsilon, k/t)$ -independent  $(|S_m|; m/t, 2^t)$  hash family.

Now we show the equivalence of  $(\epsilon, k)$ -independent sample spaces and almost strongly universal-k hash families.

**Theorem 9.** If F is an  $(\epsilon, k)$ -independent (N; m, n) hash family, then F is a  $\delta$ -ASU (N; m, n, k) hash family, where

$$\delta = \frac{(n^{-k} + \epsilon)}{n(n^{-k} - \epsilon)}.$$

*Proof.* Suppose that Eq. (2) holds. Then for any  $y_1, \dots, y_k \in B$ , we have

$$\Pr[f(x_i) = y_i, 1 \le i \le k] \ge n^{-k} - \epsilon,$$
  
$$\sum_{y_k \in B} \Pr[f(x_i) = y_i, 1 \le i \le k] \ge \sum_{y_k \in B} (n^{-k} - \epsilon), \text{ and}$$
  
$$\Pr[f(x_i) = y_i, 1 \le i \le k - 1] \ge n(n^{-k} - \epsilon).$$

From the above inequality and Eq. (2), we have

$$\frac{\Pr[f(x_i) = y_i, 1 \le i \le k]}{\Pr[f(x_i) = y_i, 1 \le i \le k-1]} \le \frac{n^{-k} + \epsilon}{n(n^{-k} - \epsilon)}.$$

Let  $\delta \stackrel{\triangle}{=} (n^{-k} + \epsilon)/(n(n^{-k} - \epsilon))$ . Then

$$|\{f \in F : f(x_i) = y_i, 1 \le i \le k\}| \le \delta \times |\{f \in F : f(x_i) = y_i, 1 \le i \le k-1\}|.$$
  
Hence, F is a  $\delta$ -ASU  $(N; m, n, k)$  hash family.

**Definition 10.** An (N; m, n) hash family F of functions from A to B is strongly  $(\epsilon, k)$ -independent if for any t such that  $1 \leq t \leq k$  and for all distinct elements  $x_1, x_2, \dots, x_t \in A$ , and for all (not necessary distinct)  $y_1, y_2, \dots, y_t \in B$ , we have

$$|\Pr(f(x_i) = y_i, 1 \le i \le t) - n^{-t}| \le \epsilon$$
(3)

where  $f \in F$  is chosen uniformly at random.

**Theorem 11.** If an (N; m, n) hash family F is strongly  $(\epsilon, k)$ -independent, then F is a  $\delta$ -ASU (N; m, n, k) hash family, where  $\delta = (n^{-k} + \epsilon)/(n^{-(k-1)} - \epsilon)$ .

Proof. The proof is similar to the proof of Theorem 9.

**Lemma 12.** [2] Suppose that a hash family F of functions from A to B is  $\epsilon$ -ASU (N; m, n, k). Then for for all  $1 \leq j \leq k$ , for all distinct elements  $x_1, x_2, \dots, x_j \in A$ , and for all (not necessary distinct)  $y_1, y_2, \dots, y_j \in B$ , we have

$$|\{f \in F : f(x_i) = y_i, 1 \le i \le j\}| \le \epsilon^j \times N \tag{4}$$

**Lemma 13.** [2] If a hash family F is  $\epsilon$ -ASU (N; m, n, k), then  $\epsilon \geq 1/n$ .

**Theorem 14.** If a hash family F is  $\epsilon$ -ASU (N; m, n, k), then F is  $(\delta, k)$ -independent, where  $\delta = (n^k - 1)(\epsilon^k - n^{-k})$ .

Proof. From Lemma 12, we have

$$\Pr[f(x_i) = y_i, 1 \le i \le k] \le \epsilon^k \quad \text{and} \tag{5}$$

$$\Pr[f(x_i) = y_i, 1 \le i \le k] - n^{-k} \le \epsilon^k - n^{-k}.$$
(6)

On the other hand, from eq.(5), we have

$$\sum_{\hat{y}_1,\cdots,\hat{y}_k)\neq(y_1,\cdots,y_k)} \Pr[f(x_i) = \hat{y}_i, 1 \le i \le k] \le (n^k - 1)\epsilon^k.$$

Therefore, we have

(

$$egin{aligned} &\Pr[f(x_i)=y_i, 1\leq i\leq k]=1-\sum_{(\hat{y}_1,\cdots,\hat{y}_k)
eq(y_1,\cdots,y_k)}\Pr[f(x_i)=\hat{y}_i, 1\leq i\leq k]\ &\geq 1-(n^k-1)\epsilon^k. \end{aligned}$$

Hence,

$$\Pr[f(x_i) = \hat{y}_i, 1 \le i \le k] - n^{-k} \ge 1 - (n^k - 1)\epsilon^k - n^{-k}$$
$$= 1 - \epsilon^k n^k + \epsilon^k - n^{-k}$$
$$= -(n^k - 1)(\epsilon^k - n^{-k}).$$

From Lemma 13, we see that  $\epsilon^k - n^{-k} \ge 0$ . Hence,

$$-(n^{k}-1)(\epsilon^{k}-n^{-k}) \leq \Pr[f(x_{i}) = \hat{y}_{i}, 1 \leq i \leq k] - n^{-k} \leq \epsilon^{k} - n^{-k}$$

Then the family is  $(\delta, k)$ -independent, where

$$\delta = \max\{|\epsilon^k - n^{-k}|, |-(n^k - 1)(\epsilon^k - n^{-k})|\} = (n^k - 1)(\epsilon^k - n^{-k})$$

#### 2.3 New multiple A-codes

By combining Propositions 2 and 8 with Theorem 9 or Theorem 11, we can obtain new multiple A-codes (ASU-k hash families) from an  $(\epsilon, k)$ -independent sample space. Since the  $(\epsilon, k)$ -independent sample spaces from [1] mentioned in Proposition 2 can be shown to be strong, we will apply Theorem 11.

**Theorem 15.** There exists a  $\delta$ -ASU (N; m, n, k) hash family where

 $\log_2 N = 2(\log_2 \log_2(m \log_2 n) + k \log_2 n - \log_2(n\delta - 1) + \log_2(k \log_2 n) - 1).$ (7)

*Proof.* Define  $l = k \log_2 n$ ,  $u = m \log_2 n$ , and

$$\epsilon = \frac{n^{-k}(\delta n - 1)}{\delta + 1} \approx n^{-k}(\delta n - 1).$$

Apply Proposition 2 and 8, constructing a strongly  $(\epsilon, k)$ -independent (N, m, n) hash family, where  $\log_2 N = 2(\log_2 \log_2 u - \log_2 \epsilon + \log_2 l - 1)$ . Now apply Theorem 11, to obtain a  $\delta$ -ASU (N; m, n, k) hash family. We compute  $\log_2 N$  as

$$\log_2 N = 2(\log_2 \log_2(m \log_2 n) - \log_2(n^{-k}(\delta n - 1)) + \log_2(k \log_2 n) - 1)$$
  
= 2(log\_2 log\_2(m log\_2 n) + k log\_2 n - log\_2(\delta n - 1) + log\_2(k log\_2 n) - 1).

### 3 A lower bound

In this section, we present a lower bound on the size of ASU-k hash families and almost k-wise independent sample spaces.

**Theorem 16.** If there exists an  $\epsilon$ -ASU(N;m,n,k) hash family such that

$$\epsilon^k \le 1/n,\tag{8}$$

then

$$N \geq \frac{1}{\epsilon^k} \left( \frac{\log\left(\frac{mn}{k-1}\right)}{\log\left(\frac{1-\epsilon^k}{\frac{1}{k}-\epsilon^k}\right)} - 1 \right).$$

**Proof.** Suppose F is an  $\epsilon$ -ASU(N; m, n, k) hash family from A to B, where |A| = m, |B| = n and  $k \ge 2$ . Construct an  $N \times mn$  binary matrix  $G = (g_{ij})$ , with rows indexed by the functions in F and columns indexed by  $A \times B$ , defined by the rule

$$g_{f,(x,y)} = \begin{cases} 1 \text{ if } f(x) = y \\ 0 \text{ if } f(x) \neq y \end{cases}$$

Interpret the columns of G as incidence vectors of the N-set F. We obtain a set-system  $(F, \mathcal{C} = \{C_{x,y} : x \in A, y \in B\})$ , where

$$C_{x,y} = \{f \in F : f(x) = y\}$$

for all  $x \in A$ ,  $y \in B$ . Let

$$t \stackrel{\Delta}{=} \lfloor \epsilon^k N \rfloor + 1. \tag{9}$$

This set-system satisfies the following properties: (A) |F| = N, (B) |C| = mn, (C)  $\sum_{C \in C} |C| = Nm$ , (D) there does not exist a subset of t points that occurs as a subset of k different blocks (see Lemma 12).

Property (D) says that (F, C) is a *t*-packing of index  $\lambda = k - 1$  (i.e., no *t*-subset of points occurs in more than  $\lambda$  blocks). Hence we obtain the following:

$$\lambda \binom{N}{t} \ge \sum_{C \in \mathcal{C}} \binom{|C|}{t}.$$
 (10)

Property (C) implies that the average block size is Nm/mn = N/n. Define a real-valued function f(x) as

$$f(x) = \begin{cases} 0 & \text{if } x < t \\ x(x-1) \dots (x-t+1) & \text{otherwise.} \end{cases}$$

Since f(x) is convex, we have

$$\frac{\lambda}{mn} \binom{N}{t} \ge \frac{1}{mn} \sum_{C \in \mathcal{C}} \binom{|C|}{t} \ge \frac{f(N/n)}{t!}$$
(11)

from Jensen's inequality. We observe that  $N/n \ge t-1$  follows from Eq. (8) and Eq. (9). Then, we obtain

$$(k-1)\frac{N(N-1)\cdots(N-t+1)}{\frac{N}{n}\left(\frac{N}{n}-1\right)\cdots\left(\frac{N}{n}-t+1\right)} \ge mn,$$
(12)

and hence

$$(k-1)\left(\frac{N-t+1}{\frac{N}{n}-t+1}\right)^t \ge mn.$$
(13)

From Eq. (9), we have  $t \leq \epsilon^k N + 1$ . Then Eq. (13) can be simplified as follows.

$$\begin{split} (k-1)\left(\frac{1-\epsilon^k}{\frac{1}{n}-\epsilon^k}\right)^t \geq mn, \quad \text{and hence} \\ (\epsilon^k N+1)\log\left(\frac{1-\epsilon^k}{\frac{1}{n}-\epsilon^k}\right) \geq \log\left(\frac{mn}{k-1}\right), \end{split}$$

from which our bound is obtained.

**Corollary 17.** Suppose  $S_m$  is an  $(\epsilon, k)$ -independent sample space. Denote  $\delta = (2^{-k} + \epsilon)/(2(2^{-k} - \epsilon))$ . If  $\delta^k \leq 1/2$ , then

$$|S_m| \ge \frac{1}{\delta^k} \left( \frac{\log\left(\frac{2m}{k-1}\right)}{\log\left(\frac{1-\delta^k}{\frac{1}{2}-\delta^k}\right)} - 1 \right).$$

*Proof.* This follows from Theorem 9.

#### 3.1 Some numerical examples of multiple A-codes

We give some numerical examples to compare the multiple A-codes constructed by Atici and Stinson in [2], our new multiple A-codes obtained from Theorem 15, and the lower bound of Theorem 16. Suppose we want an authentication code for  $m = 2^{2^{128}}$  source states with deception probability  $\delta = 2^{-40}$ . We tabulate the number of key bits (i.e.,  $\log_2 N$ ) for k = 3, 4, 10. Note that we take  $n = 2/\delta = 2^{41}$ in Theorem 15 and Theorem 16 (whereas in [2],  $n > 2/\delta$ ).

		Theorem 15	Lower bound
3	657	518	243
4	1043	602	283
10	5376	1096	523

A counter-based multiple authentication scheme would (of course) require less key bits than the proposed construction. For example, tabulated values from [2] show that the construction from [5] would for the parameters above and k = 4 require 447 key bits. Hence, the 602 - 447 = 155 additional key bits we use can be thought of as the price payed for having a stateless multiple authentication scheme. An interesting property that can be verified through Theorem 15 is the following. When  $k \to \infty$ , the number of key bits required per message approaches  $\log_2 n$ , which is the same as for the counter-based multiple authentication scheme.

## 4 Almost resilient functions

In what follows, let  $m \ge l \ge 1$  be integers and let  $\phi : \{0, 1\}^m \to \{0, 1\}^l$ .

**Definition 18.**  $\phi$  is called an (m, l, k)-resilient function if

$$\Pr[\phi(x_1, \dots, x_m) = (y_1, \dots, y_l) \mid x_{i_1} x_{i_2} \cdots x_{i_k} = \alpha] = 2^{-l}$$

for any k positions  $i_1 < \cdots < i_k$ , for any k-bit string  $\alpha$  and for any  $(y_1, \cdots, y_l) \in \{0, 1\}^l$ , where the values  $x_j$   $(j \notin \{i_1, \ldots, i_k\})$  are chosen independently at random.

Resilient functions have been studied in several papers, e.g., [10, 3, 11, 24, 4]. We now introduce a generalization, which we call  $\epsilon$ -almost resilient functions, in which the the output distribution may deviate from the uniform distribution by a small amount  $\epsilon$ .

**Definition 19.** We say that  $\phi$  is an  $\epsilon$ -almost (m, l, k)-resilient function if

$$|\Pr[\phi(x_1,...,x_m) = (y_1,...,y_l) \mid x_{i_1}x_{i_2}\cdots x_{i_k} = \alpha] - 2^{-l}| \le \epsilon$$

for any k positions  $i_1 < \cdots < i_k$ , for any k-bit string  $\alpha$  and for any  $(y_1, \cdots, y_l) \in \{0, 1\}^l$ , where the values  $x_j$   $(j \notin \{i_1, \ldots, i_k\})$  are chosen independently at random.

#### 4.1 Relation with $(\epsilon, k)$ -independent sample space

It is well-known that a resilient function is equivalent to a large set of orthogonal arrays [24]. Here we prove a similar result for almost resilient functions that involves k-wise independent sample spaces.

**Definition 20.** A large set of  $(\epsilon, k, m, t)$ -independent sample spaces, denoted  $LS(\epsilon, k, m, t)$ , is a set of  $2^{m-t}$   $(\epsilon, k, m, t)$ -independent sample spaces, each of size  $2^t$ , such that their union contains all  $2^m$  binary vectors of length m.

**Theorem 21.** If there exists an  $LS(\epsilon, k, m, t)$ , then there exists a  $\delta$ -almost (m, m-t, k)-resilient function, where  $\delta = \epsilon/2^{m-t-k}$ .

*Proof.* There are  $2^{m-t}$   $(\epsilon, k)$ -independent sample spaces in the set. Name the  $(\epsilon, k)$ -independent sample spaces  $C_{\gamma}, \gamma \in \{0, 1\}^{m-t}$ . Then define a function  $\phi: \{0, 1\}^m \to \{0, 1\}^{m-t}$  by the rule

$$\phi(x_1,\ldots,x_m)=\gamma ext{ if and only if } (x_1,\ldots,x_m)\in C_\gamma.$$

For any k positions  $i_1 < \cdots < i_k$ , any k-bit string  $\alpha$  and any  $\gamma \in \{0,1\}^{m-t}$ , let

$$L \stackrel{\Delta}{=} |\{(x_1,\ldots,x_m): x_{i_1}\cdots x_{i_k} = \alpha, (x_1,\ldots,x_m) \in C_{\gamma}\}|.$$

Then

$$\Pr[\phi(x_1, \dots, x_m) = \gamma \mid x_{i_1} x_{i_2} \cdots x_{i_k} = \alpha] = \frac{L}{2^{m-k}}.$$
 (14)

From Definition 1, we have

$$2^{-k} - \epsilon \le \frac{L}{2^t} \le 2^{-k} + \epsilon.$$
(15)

т

Hence, from (14) and (15), we obtain

$$|\Pr[\phi(x_1,\ldots,x_m)=\gamma \mid x_{i_1}x_{i_2}\cdots x_{i_k}=\alpha] - 2^{-(m-t)}| \le \frac{\epsilon}{2^{m-t-k}}.$$

**Definition 22.** The function  $\phi: \{0,1\}^m \to \{0,1\}^l$  is called *balanced* if we have

$$\Pr[\phi(x_1,\ldots,x_m)=(y_1,\ldots,y_l)]=2^{-l}$$

for all  $(y_1, \dots, y_l) \in \{0, 1\}^l$ .

For balanced functions, we can prove the converse of Theorem 21.

**Theorem 23.** If there exists a balanced  $\epsilon$ -almost (m, l, k)-resilient function,  $\phi$ , then there exists an  $LS(\delta, k, m, m-l)$ , where  $\delta = \epsilon/2^{k-l}$ .

*Proof.* For  $\gamma \in \{0, 1\}^l$ , let

$$C_{\gamma} \stackrel{ riangle}{=} \{(x_1,\ldots,x_m): \phi(x_1,\ldots,x_m)=\gamma\}.$$

Since  $\phi$  is balanced,  $|C_{\gamma}| = 2^{m-l}$ . If each  $C_{\gamma}$  is an  $(\epsilon, k)$ -independent sample space, then we automatically get a large set. For any k positions  $i_1 < \cdots < i_k$ , for any k-bit string  $\alpha$  for and any  $\gamma \in \{0, 1\}^l$ , let

$$L \stackrel{\Delta}{=} |\{(x_1,\ldots,x_m): x_{i_1}\cdots x_{i_k} = \alpha, (x_1,\ldots,x_m) \in C_{\gamma}\}|.$$

Then, within the sample space  $C_{\gamma}$ , we have

$$\Pr[x_{i_1}x_{i_2}\cdots x_{i_k} = \alpha] = \frac{L}{|C_{\gamma}|} = \frac{L}{2^{m-l}}.$$
 (16)

From Definition 19, we get

$$2^{-l} - \epsilon \le \frac{L}{2^{m-k}} \le 2^{-l} + \epsilon.$$

$$\tag{17}$$

Hence, from (16) and (17), we obtain

$$\Pr(x_{i_1}x_{i_2}\cdots x_{i_k}=\alpha)-2^{-k}|\leq \frac{\epsilon}{2^{k-l}}.$$

#### 4.2 Constructions of $\epsilon$ -almost resilient functions

**Definition 24.** An  $(\epsilon, k)$ -independent sample space  $S_m$  is *t*-systematic if  $|S_m| = 2^t$ , and there exist *t* positions  $i_1 < \cdots < i_t$  such that each *t*-bit string occurs in these positions for exactly one *m*-tuple in  $S_m$ .

A t-systematic  $(\epsilon, k)$ -independent sample space can be transformed into an  $LS(\epsilon, k, m, t)$  by using the same technique as [25, Theorem 3]. We have the following result.

**Theorem 25.** If there exists a t-systematic  $(\epsilon, k)$ -independent sample space  $S_m$ , then there exists a balanced  $\delta$ -almost (m, m - t, k)-resilient function, where  $\delta = \epsilon/2^{m-t-k}$ .

Due to space limitations, we will present only a very brief summary of our construction for t-systematic  $(\epsilon, k)$ -independent sample spaces. Our approach is similar to [12] (see also [18]), and depends on the Weil-Carlitz-Uchiyama bound. In what follows, let Tr denote the trace function from  $GF(2^t)$  to GF(2).

**Proposition 26 Weil-Carlitz-Uchiyama bound.** [9] Let  $f(x) = \sum_{i=1}^{D} f_i x^i \in GF(2^t)[x]$  be a polynomial that is not expressible in the form  $f(x) = g(x)^2 - g(x) + \theta$  for any polynomial  $g(x) \in GF(2^t)[x]$  and for any  $\theta \in F_{2^t}$ . Then

$$\left|\sum_{\alpha \in GF(2^t)} (-1)^{Tr(f(\alpha))}\right| \le (D-1)\sqrt{2^t}.$$

**Definition 27.** A polynomial  $h(x) \in GF(2^t)[x]$  is a  $(2^t, D)$ -polynomial if h has degree at most D and  $a_i = 0$  for all even i, where  $h = \sum_{i=0}^{D} a_i x^i$ . Define  $H(2^t, D, k)$  to be a set of  $(2^t, D)$ -polynomials such that any k polynomials in the set are independent over GF(2).

For  $h_{i_1}, h_{i_2}, \ldots, h_{i_k} \in H(2^t, D, k)$  and for any k elements  $\alpha_1, \cdots, \alpha_k \in GF(2)$ , define

 $N_{\alpha_1,\ldots,\alpha_k}(h_{i_1},\ldots,h_{i_k}) \stackrel{\triangle}{=} |\{x \in GF(2^t) : Tr(h_{i_1}(x)) = \alpha_1,\cdots,Tr(h_{i_k}(x)) = \alpha_k\}|.$ 

**Lemma 28.** [12]  $|N_{\alpha_1,\ldots,\alpha_k}(h_{i_1},\ldots,h_{i_k}) - 2^{t-k}| \le (D-1)\sqrt{2^t}$ .

*Proof.* The proof is an application of Proposition 26. The case k = 2 can be found in [12] and the general case is proved similarly.

**Theorem 29.** Suppose that  $\beta$  is a primitive element of  $GF(2^t)$ , and  $H(2^t, D, k)$  is chosen such that  $\{x, \beta x, \beta^2 x, \ldots, \beta^{t-1} x\} \subseteq H(2^t, D, k)$ . There exists a t-systematic  $(\epsilon, k)$ -independent sample space  $S_m$  where  $m = |H(2^t, D, k)|$  and  $\epsilon = (D-1)/\sqrt{2^t}$ .

**Proof.** Let  $H(2^t, D, k) = \{h_1, \dots, h_m\}$ . Construct a sample space  $S_m$  as follows: A binary string  $X_{\gamma} = x_1 x_2 \cdots x_m \in S_m$  is specified by any  $\gamma \in GF(2^t)$ , where the *i*th bit of  $X_{\gamma}$  is  $x_i = Tr(h_i(\gamma))$ . The proof that  $S_m$  is  $(\epsilon, k)$ -independent follows from Lemma 28. Further,  $S_m$  can be shown to be systematic using the fact that  $\{x, \beta x, \beta^2 x, \dots, \beta^{t-1} x\} \subseteq H(2^t, D, k)$  (the proof will be given in the final paper).

#### 4.3 An Application

In our approach, using Theorem 29, we need to construct a set of polynomials  $H(2^t, D, k)$  such that any k of them are linearly independent over GF(2). For this we can use linear error-correcting codes (see [14]). For a fixed (odd) degree D, we can express each polynomial as a linear combination of polynomials in the set

$$\{x, \beta x, \ldots, \beta^{t-1}x, x^3, \beta x^3, \ldots, \beta^{t-1}x^3, \ldots, x^D, \beta x^D, \ldots, \beta^{t-1}x^D\}$$

Indexing the polynomials in  $H(2^t, D, k)$  as  $h_1, h_2, \ldots, h_m$  we obtain a binary  $tD' \times m$  matrix, where D' = (D+1)/2, which is a parity check matrix of an [m, l, d] error correcting code in which m - l = tD' and d = k + 1. Conversely, given such a code, we obtain a *t*-systematic sample space, and hence a balanced  $\epsilon$ -almost (m, m - t, k)-resilient function, as follows.

**Theorem 30.** Suppose D = 2D' - 1 and there is a [m, m - tD', k + 1] code. Then there exists a balanced  $\epsilon$ -almost (m, m - t, k)-resilient function such that

$$\epsilon = \frac{(D-1)\sqrt{2^t}}{2^{m-k}}.$$

A suitable value of  $\epsilon$  would be  $2^{-m+t-1}$ . We obtain the following corollary of Theorem 30 by taking D = 3 and k = (t/2) - 2.

**Corollary 31.** Suppose there is an [m, m-4k-8, k+1] code. Then there exists a balanced  $2^{-m+2k+3}$ -almost (m, m-2k-4, k)-resilient function.

As a typical example, suppose we take m = 160 and k = 18. A [160, 80, 23] code is known to exist see ([6]), so we obtain a balanced  $2^{-121}$ -almost (160, 120, 18)-resilient function.

Let's compare the above result to the best-known (160, 120, k)-resilient function. The most important construction method for resilient functions [3, 10] uses linear error-correcting codes, as follows: Let G be a generator matrix for an [m, l, d] linear code. Define a function  $f : (GF(2))^m \mapsto (GF(2))^l$  by the rule  $f(x) = xG^T$ . Then f is an (m, l, d-1) linear resilient function. The maximum d for which a [160, 120, d] code is known to exist is d = 12 (see [6]). Hence, the maximum k for which we can construct a (160, 120, k)-resilient function is k = 11.

#### 5 Comments

The techniques of this paper can also be used to construct "almost" versions of other cryptographic tools. These include *correlation-immune functions* (see, for example, [19, 8, 7]) and *locally random pseudo-random number generators* (see [20, 16, 18]). Details will be given in the full version of the paper.

## References

- N. Alon, O. Goldreich, J. Hastad, and R. Peralta. Simple constructions of almost k-wise independent random variables. *Random Structures and Algorithms* 3 (1992), 289-304.
- M. Atici and D. R. Stinson. Universal hashing and multiple authentication. Lecture Notes in Computer Science 1109 (1996), 16-30 (CRYPTO '96).
- C. H. Bennett, G. Brassard, and J.-M. Robert. Privacy amplification by public discussion. SIAM Journal on Computing 17 (1988), 210-229.
- 4. J. Bierbrauer, K. Gopalakrishnan and D. R. Stinson. Bounds for resilient functions and orthogonal arrays. *Lecture Notes in Computer Science* 839 (1994), 247-257 (CRYPTO '94).
- J. Bierbrauer, T. Johansson, G. Kabatianskii and B. Smeets. On families of hash functions via geometric codes and concatenation. Lecture Notes in Computer Science 773 (1994), 331-342 (CRYPTO '93).
- 6. A. E. Brouwer. Bounds on the minimum distance of binary linear codes. http://www.win.tue.nl/win/math/dw/voorlincod.html
- P. Camion and A. Canteaut. Generalization of Siegenthaler inequality and Schnorr-Vaudenay multipermutations. Lecture Notes in Computer Science 1109 (1996), 372-386 (CRYPTO '96).
- P. Camion, C. Carlet, P. Charpin and N. Sendrier. On correlation-immune functions. Lecture Notes in Computer Science 576 (1992), 86-100 (CRYPTO '91).

- 9. L. Carlitz and S. Uchiyama. Bounds on exponential sums. Duke Math. Journal, (1957), 37-41.
- B. Chor, O. Goldreich, J. Hastad, J. Friedman, S Rudich and R. Smolensky. The bit extraction problem or t-resilient functions. 26th IEEE symposium on Foundations of Computer Science, pages 396-407, 1985.
- 11. J. Friedman. On the bit extraction problem. 33rd IEEE symposium on Foundations of Computer Science, pages 314-319, 1992.
- T. Helleseth and T. Johansson. Universal hash functions from exponential sums over finite fields and Galois rings. Lecture Notes in Computer Science 1109 (1996), 31-44 (CRYPTO '96).
- 13. H. Krawczyk. New hash functions for message authentication. Lecture Notes in Computer Science 921 (1995), 301-310 (EUROCRYPT '95).
- 14. F. J. MacWilliams and N. J. A. Sloane. The Theory of Error-Correcting Codes. North-Holland, 1977.
- J. L. Massey. Cryptography A selective survey. Digital Communications, North-Holland (1986), 3–21.
- U. M. Maurer and J. L. Massey. Perfect local randomness in pseudo-random sequences. Lecture Notes in Computer Science 435 (1990), 100-112 (CRYPTO '89).
- 17. J. Naor and M. Naor. Small bias probability spaces: efficient constructions and applications. SIAM Journal on Computing 22 (1993), 838-856.
- H. Niederreiter and C. P. Schnorr. Local randomness in polynomial random number and random function generators. SIAM Journal on Computing 22 (1993), 684– 694.
- T. Siegenthaler. Correlation-immunity of nonlinear combining functions for cryptographic applications. *IEEE Trans. Inform. Theory* 30 (1984), 776-780.
- C. P. Schnorr. On the construction of random number generators and random function generators. Lecture Notes in Computer Science 330 (1988), 225-232 (EURO-CRYPT '88).
- G.J. Simmons. A game theory model of digital message authentication. Congressus Numeratium 34 (1982), 413-424.
- 22. G.J. Simmons. Authentication theory/coding theory, Lecture Notes in Computer Science. 196 (1985), 411-431 (CRYPTO '84).
- 23. D. R. Stinson. Universal hashing and authentication codes. Lecture Notes in Computer Science 576 (1992), 74-85 (CRYPTO '91).
- D. R. Stinson. Resilient functions and large set of orthogonal arrays. Congressus Numerantium 92 (1993), 105-110.
- 25. D.R. Stinson and J. L. Massey. An infinite class of counterexamples to a conjecture concerning nonlinear resilient functions. *Journal of Cryptology* 8 (1995), 167–173.
- M. N. Wegman and J. L. Carter. New hash functions and their use in authentication and set equality. Journal of Computer and System Sciences 22 (1981), 265-279.