More Constructions of Lossy and Correlation-Secure Trapdoor Functions

David Mandell Freeman¹, Oded Goldreich², Eike Kiltz³, Alon Rosen⁴, and Gil Segev²

¹Stanford University, USA ²Weizmann Institute of Science, Israel ³CWI, Netherlands ⁴IDC Herzliya, Israel

> PKC 2010 Paris, France 27 May 2010

What are they and what are they good for? Previous Constructions and New Results

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LTDFs: What are they?

Functions f(x) that can behave in two ways [PW08]:

- Injective:
 - f(x) is 1-to-1.
 - There is a *trapdoor* that allows f(x) to be inverted.

2 Lossy:

- f(x) loses information: image is smaller than domain.
- If $|Domain| = 2^n$ and $|Image| = 2^{n-\ell}$, f(x) has ℓ bits of lossiness.

Security: descriptions of injective functions and lossy functions are *computationally indistinguishable*.

What are they and what are they good for? Previous Constructions and New Results

LTDFs: What are they good for?

Modular constructions of cryptographic primitives:

- Collision-resistant hash functions [PW08]
- Oblivious transfer [PW08]
- CCA-secure public-key encryption [PW08]
- Deterministic public-key encryption [BFO08]
- Security against selective opening attacks [BHY09]
- and others...

Given all these uses, we'd like to have a big "library" of LTDFs based on different computational assumptions.

What are they and what are they good for? Previous Constructions and New Results

Constructions of LTDFs

[PW08] construct LTDFs based on:

- Decision Diffie-Hellman assumption (DDH)
- Learning With Errors assumption (LWE) on lattices

We add new constructions based on:

- Quadratic Residuosity assumption (QR)
 - Apparently weaker than 2vs3primes of [MY10].
 - Generalized to eth power residuosity in full version.
- Composite Residuosity assumption (Paillier)
 - Discovered concurrently and independently by [BFO08].
- **a** *d*-*Linear* assumption
 - Simplifies and generalizes DDH construction of [PW08].

What are they and what are they good for? Previous Constructions and New Results

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Correlation-Secure Trapdoor Functions

Generalization of one-way function to correlated inputs [RS09]:

Given collection of functions \mathcal{F} and distribution \mathcal{C} on $Domain(\mathcal{F})^k$ correlation-security says that for

$$f_1, \ldots, f_k \stackrel{R}{\leftarrow} \mathcal{F}$$
 and $(x_1, \ldots, x_k) \stackrel{R}{\leftarrow} \mathcal{C},$

the function $(x_1, \ldots, x_k) \mapsto (f_1(x_1), \ldots, f_k(x_k))$ is one-way.

- Can be used to construct CCA-secure public key encryption.
- Implied by LTDFs (with any amount of lossiness [MY10]).
- Our contribution: new construction based on the hardness of *syndrome decoding*.

Outline

- Lossy and Correlation-Secure Trapdoor Functions
- 2 LTDFs from Quadratic Residuosity
- 3 LTDFs from *d*-Linear assumptions

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njective Functions Lossy Functions

Some (old) observations

N = PQ, $P \equiv Q \equiv 3 \mod 4$ prime.

- Squaring function $x \mapsto x^2 \mod N$ is lossy:
 - 4-to-1 map on $\mathbb{Z}_N^* \Rightarrow 2$ bits of lossiness.
- However, x^2 can be inverted if we know
 - **Jacobi symbol** $JS_N(x) \in \{-1, 0, 1\}$
 - Sign of x mod N (represented as integer in $-N/2, \ldots, N/2$)
- Specifically, if $(\pm x_0, \pm x_1)$ are 4 square roots of y mod N, then

$$\mathsf{JS}_N(x_0) = \mathsf{JS}_N(-x_0) = -\mathsf{JS}_N(x_1) = -\mathsf{JS}_N(-x_1).$$

So to get injective function from squaring, encode 2 extra bits in the output (e.g., Williams).

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Injective Functions Lossy Functions

Creating an injective function

Problem: how to encode extra bits in a computationally indistinguishable way.

Solution: put them in the *exponent* of *quadratic non-residues*.

Define:

$$h(x) := \begin{cases} 1, & \text{if } x \mod N > 0 \\ 0, & \text{if } x \mod N < 0 \end{cases} \quad j(x) := \begin{cases} 1, & \text{if } JS_N(x) = -1 \\ 0, & \text{if } JS_N(x) = 0 \text{ or } 1 \end{cases}$$

Choose $r, s \in \mathbb{Z}_N^*$ with $JS_N(r) = -1$, $JS_N(s) = 1$, s a quadratic non-residue. Then injective function is

$$f_{r,s,N}(x) = x^2 \cdot r^{j(x)} \cdot s^{h(x)} \mod N.$$

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Injective Functions Lossy Functions

Recovering the extra bits

$$\begin{split} f_{r,s,N}(x) &= x^2 \cdot r^{j(x)} \cdot s^{h(x)} \mod N \\ h(x) &:= \begin{cases} 1, & \text{if } x \mod N > 0 \\ 0, & \text{if } x \mod N < 0 \end{cases} \quad j(x) &:= \begin{cases} 1, & \text{if } JS_N(x) = -1 \\ 0, & \text{if } JS_N(x) = 0 \text{ or } 1 \end{cases} \\ JS_N(r) &= -1, \quad JS_N(s) = 1, \quad s \text{ a quadratic non-residue} \end{cases}$$

To learn $JS_N(x)$:

$$\mathsf{JS}_{N}(f_{r,s,N}(x)) = \mathsf{JS}_{N}(r^{j(x)}) = \mathsf{JS}_{N}(x).$$

To learn the sign of x:

$$f_{r,s,\mathcal{N}}(x)\cdot r^{-j(x)}=x^2\cdot s^{h(x)}$$
 is a quadratic residue $\Leftrightarrow h(x)=0.$

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Injective Functions Lossy Functions

Inverting injective functions

$$f_{r,s,N}(x) = x^2 \cdot r^{j(x)} \cdot s^{h(x)} \mod N$$

Given the factorization of N, we can invert $f_{r,s,N}(x)$ by:

• Compute $JS_N(f_{r,s,N}(x))$ to learn $JS_N(x)$.

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- Compute $JS_N(f_{r,s,N}(x))$ to learn $JS_N(x)$.
- 2 Multiply by $r^{-j(x)}$.

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- 2 Multiply by $r^{-j(x)}$.
- **③** Determine whether result is a quadratic residue to learn h(x).
- Multiply by $s^{-h(x)}$.
- Compute four square roots and output the one that matches h(x), j(x).

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Injective Functions Lossy Functions

Creating lossy functions

$$f_{r,s,N}(x) = x^2 \cdot r^{j(x)} \cdot s^{h(x)} \mod N$$

 $\mathsf{JS}_N(r) = -1$, $\mathsf{JS}_N(s) = 1$, s a quadratic non-residue

To create a lossy function, choose s with $JS_N(s) = 1$ and s a *quadratic residue*.

- Function $f_{r,s,N}(x)$ is now 2-to-1 (one bit of lossiness) loses information about the sign of x.
- Lossy functions $f_{r,s,N}$ are indistinguishable from injective functions $f_{r,s,N}$ under *quadratic residuosity assumption*.

Extending the system

Functions with index-independent domains (necessary for some applications):

• Can achieve $\log_2(4/3)$ bits of lossiness.

Using eth power residuosity assumption for e > 2:

- Can achieve log₂(e) bits of lossiness for e < N^{1/4} with small prime factors.
- Inversion uses *Eisenstein reciprocity* in number fields.

See full version at http://eprint.iacr.org/2009/590 for details.

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Outline

Motivating observations The construction

- Lossy and Correlation-Secure Trapdoor Functions
- 2 LTDFs from Quadratic Residuosity
- **③** LTDFs from *d*-Linear assumptions

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Motivating observations The construction

A motivating observation

View $x \in \{0,1\}^n$ as a length-*n* vector \vec{x} . Let *M* be an $n \times n$ matrix over \mathbb{F}_p . Consider

$$f_M(\vec{x}) := M \cdot \vec{x} \in \mathbb{F}_p^n$$

This function can be lossy or injective!

Injective:

- If M has rank n, then $f_M(x)$ is invertible.
- Need to know M^{-1} to invert.

2 Lossy:

- If M has rank d, then $f_M(x)$ has image of size at most p^d .
- If $p^d < 2^n$ then image is smaller than domain.

But we can easily distinguish these two cases by computing rank(M).

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Making injective and lossy functions indistinguishable

Idea: encode *M* in *exponent* of a group where discrete log is hard.

 $\mathbb{G}= ext{ group of order p}, \hspace{1em} g ext{ a generator}, \hspace{1em} M=(m_{ij})\in \mathbb{F}_p^{n imes n}$

Function description is $g^M := (g^{m_{ij}}) \in \mathbb{G}^{n \times n}$; trapdoor is M^{-1} .

- Evaluation:
 - $f_{g^M}(\vec{x}) := g^{M \cdot \vec{x}} \in \mathbb{G}^n$.
 - Can be easily computed from g^M and \vec{x} .

• Inversion (if *M* is full rank):

- **(**) Apply M^{-1} in exponent to recover $g^{ec x} \in \mathbb{G}^n$ (also easy).
- 2 Take discrete logs to recover \vec{x} (easy since $\vec{x} \in \{0, 1\}^n$).

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Security

Theorem [BHHO08,NS09]: if *d-linear assumption* holds in \mathbb{G} , then

$$\{g^M : rank(M) = n\}$$
 and $\{g^M : rank(M) = d\}$

are computationally indistinguishable.

- *d*-Linear assumption: generalization of DDH that may hold in groups with a *d*-linear map [BBS04,HK07,S07].
- d = 1 is DDH; d = 2 is "decision linear."

When rank(M) = d, amount of lossiness is $n - d \log_2 p$ bits.

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Motivating observations The construction

Observations and extensions

- Simplifies and generalizes [PW08] ElGamal-based construction
 - Save space by using random M instead of $M \in \{0,1\}^{n \times n}$.
 - Avoid generalized ElGamal encryption (d times as large).
- ② Can choose parameters to achieve varying amounts of lossiness.
- Solution Admits an "all-but-one" generalization (DDH only).
 - Needed for [PW08] construction of CCA-secure encryption.
 - Details in full paper.

Conclusions

Motivating observations The construction

We showed constructions of lossy trapdoor functions based on *quadratic residuosity* and *d-Linear* assumptions.

• Also in paper: *composite residuosity* (Paillier) assumption, correlation-security from *syndrome decoding*.

Expanding our "library" of LTDFs expands the methods we have for creating cryptosystems in a simple and modular way.

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