Generalized Correlation Analysis of Vectorial Boolean Functions

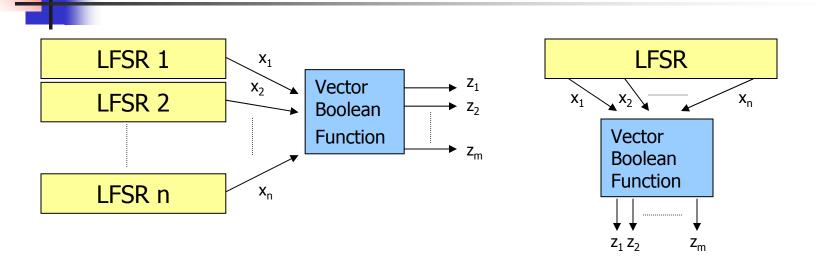
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Introduction



- In this talk, we shall improve correlation attacks on vectorial stream ciphers.
- Will consider vectorial Boolean functions in combinatorial and filtering generators.
 - Will not go into the details of the correlation attack.
- Focus on how to obtain good linear approximation.

Correlation Attack of Vectorial Stream Ciphers



• In standard correlation attack of vectorial Boolean functions, we form linear approximation of the form:

$$\Pr(b_1 z_1 \oplus \cdots \oplus b_m z_m = w_1 x_1 \oplus \cdots \oplus w_n x_n) = \Pr(b \cdot z = w \cdot x).$$

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Linear Bias and Nonlinearity

For correlation attack to succeed, we require

Bias =
$$|\Pr(b \cdot z = w \cdot x) - 1/2|$$
 to be high.

where z = F(x) is the output. I.e. probability far away from $\frac{1}{2}$.

This is equivalent to the condition that nonlinearity

$$N_F = 2^{n-1} - \frac{1}{2} \max_{w \neq 0, b} \left| \sum_{x \in GF(2)^n} (-1)^{b \cdot F(x) + w \cdot x} \right| \text{ is low,}$$

Zhang-Chan Attack

At Crypto 2000, Zhang and Chan noticed that z=F(x) is known, therefore we can consider

$$\Pr(g(z) = w_1 x_1 \oplus \cdots \oplus w_n x_n) = \Pr(g(z) = w \cdot x)$$

which is linear in x for any Boolean function $g(\cdot)$.

Because approximation of $b \cdot z$ is a particular case of approximation of g(z). It is easier to get a better linear approximation, i.e. get $\Pr(g(z)=w \cdot x)$ further away from $\frac{1}{2}$ than $\Pr(b \cdot z=w \cdot x)$.

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Zhang-Chan Attack

For Zhang-Chan attack to succeed, we require $Bias = \left| \Pr(g(z) = w \cdot x) - 1/2 \right| \text{ to be high.}$

where z=F(x) is known.

This is equivalent to the condition that unrestricted nonlinearity

$$UN_F = 2^{n-1} - \frac{1}{2} \max_{w \neq 0, g(\cdot)} \sum_{\mathbf{x} \in GF(2)^n} (-1)^{g(F(\mathbf{x})) + w \cdot \mathbf{x}} \text{ is low,}$$

Generalized Correlation

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Generalized Correlation Attack

- We still want to get approximations which are linear in x.
- The most general approximation which is linear in x:

$$\Pr(g(z) = w_1(z)x_1 \oplus \cdots \oplus w_n(z)x_n) = \Pr(g(z) = w(z) \cdot x)$$

where $w_i(z)$ are Boolean functions of the known output z and $w(z)=(w_1(z),...,w_n(z))$

Generalized Correlation Attack

For generalized correlation attack to succeed, we require

Bias =
$$|\Pr(g(z) = w(z) \cdot x) - 1/2|$$
 to be high.

where z=F(x) is known.

This is equivalent to the condition that generalized nonlinearity

$$GN_F = 2^{n-1} - \frac{1}{2} \max_{w(\cdot) \neq 0, g(\cdot)} \sum_{x \in GF(2)^n} (-1)^{g(F(x)) + w(F(x)) \cdot x} \text{ is low,}$$

Generalized Correlation Attack

- $g(z)=w(z)\cdot x$ is a more general approximation than $g(z)=w\cdot x$, which in turn is a more general approximation than $b\cdot z=w\cdot x$.
- Therefore $Pr(g(z)=w(z)\cdot x)$ can be chosen to be further away from ½ than the other two approximations.
- In terms of nonlinearities,

$$GN_F \le UN_F \le N_F$$

From a Cipher Designer's Viewpoint

• From the viewpoint of a stream cipher designer, he needs to ensure generalized nonlinearity GN_F is high for protection against correlation attack. Then automatically, UN_F and N_F will be high.

Comparison of Generalized Correlation Attack with Known Methods

An Example on Bent Functions

$x = x_1 x_2 x_3 x_4$	0000	0001	0010	0011	0100	0101	0110	0111
$F(x) = (z_1 z_2)$	00	00	00	00	00	01	10	11
$x = x_1 x_2 x_3 x_4$	1000	1001	1010	1011	1100	1101	1110	1111
$F(x) = (z_1 z_2)$	11	00	10	01	11	01	00	10

- F(x) is a bent function from $GF(2)^4$ to $GF(2)^2$. We have N_F =6 and UN_F =5. This means the best affine approximation has probability 0.63 and 0.69 for usual and Zhang-Chan.
- For generalized correlation attack, we have GN_F =2. The best generalized approximation has probability:

$$Pr(z_1 + z_2 = (z_1 + 1)(z_2 + 1)x_2 + z_1x_3 + z_2x_4) = 0.88$$



Below is a table comparing average nonlinearities of 10000 randomly generated balanced functions from n-bits to n/2-bits:

n	6	8	10	12	14
N_F	18	100	443	1897	7856
UN_F	16	88	407	1768	7454
GN_F	6	36	213	1101	5224

 GN_F is much lower than N_F and UN_F



Here's the table for average best approximation probability of the previous functions from n-bits to n/2-bits:

n	6	8	10	12	14
Probability	0.72	0.61	0.57	0.54	0.52
(usual)					
Probability	0.75	0.66	0.60	0.57	0.55
(Zhang-Chan)					
Probability	0.91	0.86	0.79	0.73	0.68
(generalized)					

Probability of generalized attack much further away from 0.5 than the other attacks

Another Example on Inverse Function

Let us compare the various approximation probability for x^{-1} on GF(2⁸) restricted to m output bits.

m	1	2	3	4	5	6	7
Probability (usual)	0.56	0.56	0.56	0.56	0.56	0.56	0.56
Probability (Zhang-Chan)	0.56	0.58	0.61	0.63	0.67	0.73	0.78
Probability (generalized)	0.56	0.69	0.74	0.84	1.00	1.00	1.00

Computation of Generalized Nonlinearity

Computation of Generalized Nonlinearity

 Since we saw that generalized correlation attack is more powerful than known attacks, it is useful to compute the generalized nonlinearity.

$$GN_F = 2^{n-1} - \frac{1}{2} \max_{w(\cdot) \neq 0, g(\cdot)} \sum_{x \in GF(2)^n} (-1)^{g(F(x)) + w(F(x)) \cdot x}$$

We need to compute

$$\sum_{x \in GF(2)^n} (-1)^{g(F(x)) + w_1(F(x)) x_1 + \dots + w_n(F(x)) x_n}$$

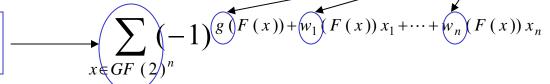
over all choices of $g, w_1, ..., w_n$: GF(2)^m \rightarrow GF(2).

Computation of Generalized Nonlinearity

We need to compute

Each of these n+1 functions have 2²^m choices

Each sum has complexity 2ⁿ



over all choices of $g, w_1, ..., w_n$: GF(2)^m \rightarrow GF(2).

Therefore complexity is approximately

$$\left(2^{2^m}\right)^{n+1} \times 2^n = 2^{2^m(n+1)+n}$$

More Efficient Computation of Generalized Nonlinearity

Theorem: The generalized nonlinearity

$$GN_F = 2^{n-1} - \frac{1}{2} \max_{w(\cdot) \neq 0, g(\cdot)} \sum_{x \in GF(2)^n} (-1)^{g(F(x)) + w(F(x)) \cdot x}$$

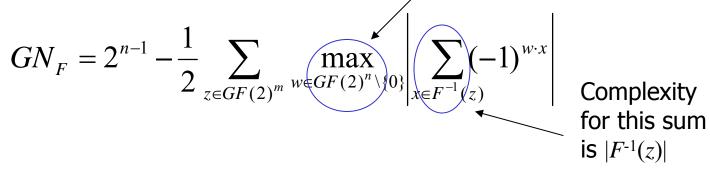
can be computed as

$$GN_F = 2^{n-1} - \frac{1}{2} \sum_{z \in GF(2)^m} \max_{w \in GF(2)^n \setminus \{0\}} \left| \sum_{x \in F^{-1}(z)} (-1)^{w \cdot x} \right|$$

Here we do not find the optimal functions $w_1(),...,w_n()$ and g(), instead we just find an optimal vector $w \in GF(2)^n \setminus \{0\}$ at each z.



 2^{n} -1 choices for w



- The new complexity for computing generalized nonlinearity is $\sum_{z \in GF(2)^m} (2^n 1) \times |F^{-1}(z)| = (2^n 1)2^n \approx 2^{2n}$
- This is much faster compared to original complexity of $2^{2^m(n+1)+n}$

Upper Bound on Generalized Nonlinearity

Upper Bound

Theorem: If F(x) is balanced, then an upper bound for GN_F :

$$GN_F \le 2^{n-1} - 2^{n-1} \sqrt{\frac{2^m - 1}{2^n - 1}}$$

■ This is much lower than the known upper bounds for unrestricted nonlinearity UN_F and nonlinearity N_F :

$$UN_{F} \leq 2^{n-1} - \frac{1}{2} \left(\frac{2^{2m} - 2^{m}}{2^{n} - 1} + \sqrt{\frac{2^{2n} - 2^{2n-m}}{2^{n} - 1} + \left(\frac{2^{2m} - 2^{m}}{2^{n} - 1} - 1 \right)^{2}} - 1 \right)$$

$$N_{F} \leq 2^{n-1} - 2^{n/2 - 1}$$



For $m \le n/2$, the upper bound for unrestricted nonlinearity UN_F does not improve on the Covering Radius Bound $2^{n-1}-2^{n/2-1}$.

The upper bound for generalized nonlinearity GN_F does.

Comparison of Upper Bound for N_F,UN_F and GN_F

n	6	8	10	12	14	16
m=n/2	3	4	5	6	7	8
Upp Bd N_F	28	120	496	2016	8128	32640
$Upp Bd \\ UN_F$	29	121	497	2017	8129	32641
Upp Bd GN_F	22	97	423	1794	7471	30724

Corresponding Bound for Probability of Best Approximation

n	6	8	10	12	14	16
m=n/2	3	4	5	6	7	8
Probability (usual)	≥0.563	≥0.531	≥0.516	≥0.508	≥0.504	≥0.502
Probability (Zhang-Chan)	≥0.558	≥0.530	≥0.515	≥0.508	≥0.504	≥0.502
Probability (generalized)	≥0.667	≥0.621	≥0.587	≥0.562	≥0.544	≥0.531



For m>n/2, the upper bound for unrestricted nonlinearity UN_F does improve on the Covering Radius Bound but not by much.

The upper bound for generalized nonlinearity GN_F improves on the Covering Radius bound 2^{n-1} - $2^{n/2-1}$ by much more.

Comparison of Upper Bound for N_F,UN_F and GN_F

n	6	8	10	12	14	16
m=3n/4	4	6	7	9	10	12
Upp Bd N_F	28	120	496	2016	8128	32640
$Upp Bd \\ UN_F$	27	110	487	1972	8090	32460
Upp Bd GN_F	17	65	332	1325	6145	24577

Corresponding Bound for Probability of Best Approximation

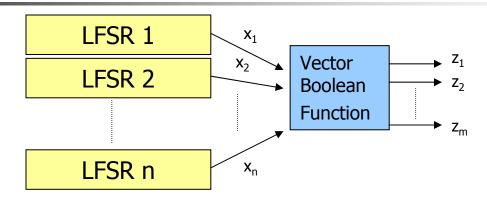
n	6	8	10	12	14	16
m=3n/4	4	6	7	9	10	12
Probability (usual)	≥0.563	≥0.531	≥0.516	≥0.508	≥0.504	≥0.502
Probability (Zhang-Chan)	≥0.587	≥0.571	≥0.524	≥0.519	≥0.506	≥0.505
Probability (generalized)	≥0.744	≥0.749	≥0.676	≥0.677	≥0.625	≥0.625



Thus we have further evidence that generalized correlation attack is more effective than Zhang-Chan and usual correlation attack on vector Boolean functions.

Generalized Resiliency

Siegenthaler's Attack



- Suppose there exists a correlation $Pr(x_1=z_1\oplus z_2)=\frac{3}{4}$.
- Then we guess the content of LFSR1
- If our guess is correct, LFSR1 sequence matches the known keystream $z_1 \oplus z_2$ with probability $\frac{3}{4}$.
- If not, LFSR1 sequence matches the keystream with probability ½.
- Reduction in attack complexity: Instead of attacking all LFSR's simultaneously, we attack one LFSR separately and then the others.

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Resiliency

- To prevent against the previous attack, we want to avoid linear approximations which involve too few input variables.
- A function $F:GF(2)^n \rightarrow GF(2)^m$ is called correlation immune of order k if

$$\Pr(b \cdot z = w \cdot x) = \frac{1}{2}$$

for all $b \in GF(2)^m \setminus \{0\}$ whenever $1 \le wt(w) \le k$. If furthermore, F(x) is balanced, then we say F(x) is k-resilient.

Generalized Siegenthaler's Attack

Suppose for a set of output vectors, e.g. z = 0000, 0001, 0010, 0111,... there exists good approximations

$$Pr(L_1(x,z)=0) = p_1 \neq \frac{1}{2}, Pr(L_2(x,z)=0) = p_2 \neq \frac{1}{2},...$$

which are linear in x and involve only k variables $x_1,...,x_k$ (where k is small) out of n variables $x_1,...,x_n$.

• We can attack k LFSR's instead of all n LFSR's. E.g. guess the contents of the k LFSR's and see if they satisfy the approximations

$$Pr(L_1(x,z)=0) = p_1 \neq 1/2, Pr(L_2(x,z)=0) = p_2 \neq 1/2,...$$

Generalized Resiliency

- To prevent against the previous attack, we want to avoid linear approximations $Pr(L(x,z)=0)=p\neq \frac{1}{2}$ which involve too few input variables $x_1,...,x_n$ for any subset of output z.
- A function $F: GF(2)^n \to GF(2)^m$ is called generalized correlation immune of order k if for all $z \in GF(2)^m$

$$Pr(g(z) \oplus w_1(z)x_1 \oplus ... \oplus w_n(z)x_n) = \frac{1}{2}$$

whenever $\operatorname{wt}(w_1(z), ..., w_n(z)) \le k$. If furthermore, F(x) is balanced, then we say F(x) is generalized k-resilient.



Equivalence between Resiliency and Generalized Resiliency

- **Theorem:** A function $F:GF(2)^n \to GF(2)^m$ is correlation immune of order k if and only if it is generalized correlation immune of order k.
- The above statement is true if we replace correlation immune with resilient.

Generalized Nonlinearity of Secondary Constructions

Output Composition

It is common to form balanced highly nonlinear vectorial functions by dropping output bits of a highly nonlinear permutation, e.g. x^{-1} , $x^{2^{k+1}}$. The nonlinearity N_F is preserved in this case.

We prove the following generalization.

- **Proposition:** Let $F:GF(2)^n \to GF(2)^m$ and $G:GF(2)^m \to GF(2)^k$ be balanced vector functions. Then $GN_{G^{\circ}F} \ge GN_F$.
- If G(x) is a permutation, then $GN_{G^{\circ}F} = GN_F$.



Concatenation

- By our previous result, a resilient function is also generalized resilient.
- Therefore we would like to check that secondary constructions for resilient functions yield high generalized nonlinearity.
- A secondary construction for resilient function we will look at is concatenation.

Concatenation

- **Proposition (Zhang-Zheng):** Let $F:GF(2)^n \to GF(2)^m$ be t_1 -resilient and $G:GF(2)^p \to GF(2)^q$ be t_2 -resilient. Then $H:GF(2)^{n+p} \to GF(2)^{m+q}$ defined by H(x,y) = (F(x),G(y)) is a t-resilient function where $t = \min(t_1,t_2)$.
- **Proposition:** For H(x,y) as defined above:

$$GN_H \le 2^{n+p-1} - \frac{1}{2}(2^n - 2GN_F)(2^p - 2GN_G)$$

Thus for H(x,y) to have high generalized nonlinearity, both component functions F(x) and G(y) must have high generalized nonlinearity.