

# Modeling of Dependence in Impulsive Interference and Copula Theory





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# 1. Modeling of Interference

- 2. Copula Theory
- 3. System Model
- 4. Simulations







# **Interference Model**

- I. Classic Gaussian Model:
- 1) Impulsiveness ---- low tail probability
- 2) Dependence --- i.i.d
- **II. Modeling of Impulsiveness**

Alpha-stable Model --- long tail in PDF

- **III. Modeling of Dependence:**
- 1) Sub-Gaussian Model
- 2) Copula Theory



## Alpha-stable model:

Network Geometry --- PPP (Poisson Point Process)

Aggregate interference ---  $\alpha$ -Stable<sup>[1]</sup>.

- 1) Characterizes impulsivness
- 2) Captures the characteristics of network geometry

[1] ILOW, Jacek et HATZINAKOS, Dimitrios. Analytic alpha-stable noise modeling in a Poisson field of interferers or scatterers. *IEEE transactions on signal processing*, 1998, vol. 46, no 6, p. 1601-1611..

# **Chrs** Modeling of Interference

# Dependence of interference in wireless network

#### Two determinants of interference<sup>[2]</sup>:

**1. Path Law**, e.g. SIMO – strong interference received on one antenna  $\rightarrow$  strong one on another antenna.

#### 2. Network Geometry, (concurrently transmitting nodes).

- (1) the distribution of nodes
- (2) the multiple access scheme. E.g. SCMA

[2] Weber, Steven, and Jeffrey G. Andrews. "Transmission capacity of wireless networks." *Foundations and Trends*<sup>®</sup> *in Networking*5.2–3 (2012): 109-281.





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#### Question : What is copula?

#### 1. Sklar's Theorem:

If  $F(X_1, ..., X_n)$  is joint distributed function with margins  $F_1(X_1), ..., F_n(X_n)$ , there exists a (Copula) function C such that

$$F(X_1,...,X_n) = C(F_1(X_1),...,F_n(X_n))$$
(2-1)

where C is unique if F and G are continuous, otherwise C is uniquely determined on  $Ran(F_1) \times \cdots \times Ran(F_n)$ .

$$C(U_1,...,U_n) = F(F_1^{-1}(U_1),...,F_n^{-n}(U_n))$$
(2-2)





Question : What is copula?

**2. PDF of**  $\vec{X} = (X_1, ..., Xn)$ :

$$f(X_1,...,X_n) = c(f(X_1),...,f(X_n)) \prod_{k=1}^n f(X_k)$$
(2-3)  
Dependent component

Independent component

$$c(u_1,...,u_n) = \frac{\partial^n C(u_1,...,u_n)}{\partial u_1...\partial u_n}$$
(2-4)





#### Question : why copula?

3. Receiver:

In a BPSK system, the received signal is:

$$\vec{Y}_N = \vec{S}_N + \vec{Z}_N \tag{2-5}$$

 $S_N \quad \text{---- vector containing repeated samples } s = \pm 1,$ 

 $\overline{Z}_N$  ---- interference vector.

Log likelihood ratio (LLR) will be:

$$\wedge (\vec{Y}_{N}) = \log \frac{P(z_{1} = y_{1} - 1, ..., z_{N} = y_{N} - 1 | s = +1)}{P(z_{1} = y_{1} + 1, ..., z_{N} = y_{N} - 1 | s = -1)}$$

$$= \log \frac{f_{\vec{Z}_{N}}(y_{1} - 1, ..., y_{N} - 1)}{f_{\vec{Z}_{N}}(y_{1} + 1, ..., y_{N} + 1)}$$
(2-6)
where *f* is the joint PDF of  $\vec{Z}_{K}$ .



Question : Relation between copula and our research

#### 3. Receiver:

Hence, the LLR becomes:





(2-7)



#### 4. Student (t) copula:

$$C_{\nu,\Sigma}(u_1,...,u_n) = F(F_1^{-1}(u_1),...,F_1^{-n}(u_n))$$
(2-8)

where 
$$F \sim T_n(0, \Sigma, v)$$
 and  $F_1 \sim T(v)$   
 $c_{v,\Sigma}(\vec{u}) = \frac{f(t^{-1}(u_1), ..., t^{-1}(u_n))}{\prod_{i=1}^n f_1(t^{-1}(u_i))}$ 
(2-9)

where f and  $f_1$  are densities for n and 1 dimension

- 1. Flexibility and wide range of dependence --  $\nu$  ,  $\Sigma$
- 2. Extendable
- 3. Closed-form or computationally feasible,









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# **Model** (PPP with $\lambda$ ):

1. Each device transmits over a subset of orthogonal bands  $B = \{1, ..., K\}$ 

- 2. Each time *t*, devices independently transmit on a band  $k \in B$  with probability p
- 3. Devices on band  $k \rightarrow thinning PPP$  wih  $p\lambda$

$$Z_{k}(t) = \sum_{j \in \Phi_{k}(t)} r_{j}(t)^{-\eta/2} h_{j,k}(t) x_{j,k}(t), \quad k = 1, ..., K$$
(3-1)





Interference is

$$Z_{k}(t) = \sum_{j \in \Phi_{k}(t)} r_{j}(t)^{-\eta/2} h_{j,k}(t) x_{j,k}(t), \quad k = 1, ..., K$$
(3-1)

 $\begin{array}{l} h_{j,k}\left(t\right) \sim CN(0,1) \quad ---- \text{ Rayleigh fading of device } j \text{ on band } k \\ r_{j}\left(t\right) \quad ---- \text{ distance to the access point} \\ \eta \quad ---- \text{ path-loss exponent} \\ \Phi_{k}\left(t\right) \quad ---- \text{ PPP with } p\lambda \end{array}$ 

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1.  $Z_k = z_{k,r} + i \cdot z_{k,i}$  is an isotropic complex  $\alpha$ -stable variable, where  $\alpha = 4/\eta$ .

$$\vec{Z}_{k} = (z_{k,r}, z_{k,i}) = A^{1/2} (G_{1}, G_{2})$$
 (3-2)

 $\vec{Z}_k = A^{1/2}(G_1, G_2)$  is sub-Gaussian, where

$$A \sim S_{\alpha/2} \left( \cos \left( \frac{\pi}{4} \alpha \right)^{2/\alpha} , 1, 0 \right)$$
 ----- skewed  $\alpha$ -stable

 $G_1$ ,  $G_2$  ---- independent Gaussian variables, i.e  $(G_1, G_2) \sim CN(0, \sigma^2 I)$ 





## Scenario --- General SCMA codebook

2. Stacking real and imaginary parts, we have the 2k dimensional interference vector

$$\vec{Z}_{2K} = \left( z_{1,r}, z_{1,i}, \dots, z_{K,r}, z_{K,i} \right)$$
(2-3)

Sub–Gaussian for *p*=1.

Dependence structure remains unspecified (0<p<1).







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Each of these devices (following PPP) transmits on each band *k*=1,...,K with probability *p*. *p*K ---- the average quantity of frequency resources used by

each device per transmission .





Figure 1. Real and Imaginary Parts of Interference

- 1. Isotropic
- 2. Conditionally Gaussian
- 3. Strong dependence in impulsiveness









Figure 2. Real Parts of Interference on different bands









Figure 3. Density of margins of  $\alpha$ -stable interference

Figure 4. Density of *t* copula function

T copulas with different v have similar densities.





- 1. Monte Carlo Method --- (Test) Data set
- 2. Stable fit & T Copula fit --- Estimating Model Parameters
- 3. Generating datas under the model with the estimated parameters --- (Model) Data Set
- 4. KL-divergence between **Test Set** and **Model Set**.

Three models are compared:

- 1. t copula
- 2. 2-dimensional sub=Gaussian
- 3. Sub-Gaussian

$$\vec{Z}_{2K} = (z_{1,r}, z_{1,i}, ..., z_{K,r}, z_{K,i})$$







Figure 5. KL divergence of  $\overrightarrow{Z_K} = (z_{1,r}, ..., z_{K,r})$  under different p, K=8



Corres Simulation 5. 
$$\vec{Z}_{2K} = (z_{1,r}, z_{1,i}, ..., z_{K,r}, z_{K,i})$$
 with  $p=1$ 



Figure 6. KL divergence of  $\overrightarrow{Z_{2K}} = (z_{1,r}, \dots, z_{2K,r})$  under different K, p=1



**Chris Simulation 6.**  $\vec{Z}_{2K} = (z_{1,r}, z_{1,i}, ..., z_{K,r}, z_{K,i})$ , K=2 and 8



Figure 7. KL divergence of  $\overrightarrow{Z_{2K}} = (z_{1,r}, \dots, z_{2K,r})$  under different *p*, K=2 and K=8













