Tri-Variate Copula Modeling for Spatially Correlated Observations in Wireless Sensor Networks

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Abstract — Correlated Observations arise in Wireless Sensor Networks (WSNs) comprising of crowded sensor nodes monitoring a common physical phenomenon. Correlation exists both in spatial and time domain, numerous models have addressed linear dependency in sensor observations. However, Copulas model both linear as well as non-linear dependency in spatial domain. In this paper we have proposed a fusion model for generalized case using Copulas and evaluated it for a tri-variate case. A 3D Copula model previously introduced is computed and analyzed based on Neyman-Pearson framework. Gaussian and Student-t Copulas demonstrate a superior performance for spatially correlated observations as compared to Chair-Varshney rule for independent observations.

Index Terms — Wireless sensor networks, distributed detection, spatial correlation, copula, fusion, Tri-variate.

I. INTRODUCTION

Wireless Sensor Networks is composed of randomly deployed sensor nodes and the main aim lies in detection of events. Events like landslides, forest fires, earthquakes, tsunamis, etc. [1] may cause damage to human lives if not detected accurately. WSNs can be implemented for continuous monitoring and detection of such events, but scenarios in this case require high density of sensor nodes. Detection, parameter estimation or tracking are the main tasks in applications of WSNs. The main aim of any sensing system is detection of event. For example, in the cases of environmental monitoring, it is of interest to first detect the location of forest fire, before determining the extent of fire spread. For systems observing rare events such as surveillance systems, detection of event is always necessary.

Detection of such events, result into correlated observations in space and as well as time domain. A survey on decentralized detection by authors in [2] illustrated that dependent randomization requires larger co-ordination between sensors. Such co-ordination can be carried off-line and no additional online communication is required. Authors in [3] started preliminary work on distributed detection with fusion as an active research area. The goal was to design a theoretical framework for detection with distributed sensors due to disadvantages of centralized scheme. Wherein for Centralized scheme computational complexity of the Fusion Center increases tremendously. Also most of the previous analysis is carried out for statistically independent observations. Given the hypothesis, Likelihood Ratio Test (LRT) for local sensor decision rules under the Bayesian and Neyman-Pearson criterion is proved in [4]. When assumption of conditional independence does not hold problems tend to be more complex. This is illustrated in [5] where authors designed a distributed detection system and studied the effect of correlated noise on system performance. Assuming local sensors have same operating point and symmetric distribution, signal detection is done. Detection of known signal in additive Gaussian and Laplacian noise is considered but, the observations resulted into performance loss. Thus distributed detection with conditionally dependent observations is known to be a stimulating problem. Towards this end design of fusion rules using correlated decisions has been considered. A new approach is discussed taking into account spatial correlation and constraining the local sensors to be binary quantizers. This problem is analyzed in [6] and they proposed a novel method to fuse correlated sensor decisions obtained by binary quantization. Proposed work used Neyman Pearson framework based on Copula theory to construct joint density of sensor observations. Use of Gaussian and Student-t copulas is also discussed. However authors in this paper focused on two sensor design analysis. In [7] event detection problem is considered, where sensors are designed as uniform multilevel quantizers. Analysis is done for two sensor case using copula theory for fusion of data. Also extension for N sensor case is done which illustrates evaluating N dimensional integrals thereby increasing computational processing. In [8] Copula based models are suggested for spatial interpolation to analyze traffic flow from remote microwave sensors. Results of copula-based models are compared with three kriging methods. Results illustrate that for complex traffic conditions Copula-based models are more effective and are also insensitive to the effects of temporal changes. Further a tri-variate model is developed in [9] using R-vine decomposition. But the model evaluated and analyzed multivariate copulas using a cascade of bivariate copulas.

Hence considering above limitations we tried to develop a framework for independent as well as dependent observations using Copulas. And also have formulated a mathematical framework using Log-Likelihood Ratio test for fusion statistics of sensor

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observations considering generalized case. Further simulations are carried out and analyzed for 3D copula model and Chair-Varshney rule.

II. PROBLEM FORMULATION

A hypothesis testing problem is considered for detection of a random source deploying a wireless sensor network. Hypothesis \( H_1 \) indicates presence of random source and \( H_0 \) absence of source. Sensor observations due to higher density bound to be correlated, also spatial correlation increases with decrease in node separation. Sensor observations under \( H_1 \) will be always correlated and for \( H_0 \) may or may not be correlated. Considering sensor observations are dependent in spatial domain and independent with respect to time. Sensor nodes in the network are programmed as binary quantizers which convert the sensor observation \( x_{in} \) to the quantized value \( u_i \) (sensor decision) based on the threshold \( \tau \) declaring presence or absence of an event [3]. Here \( L \) refers to the number of sensors (i.e., \( i = 1,2 \cdots L \) ) and \( N \) refers to the number of time instants (i.e., \( n = 1,2 \cdots N \)).

\[
u_i = \begin{cases} 0 & -\infty \leq x_{in} \leq \tau \quad H_0 \text{ is said to be declared} \\ 1 & \tau \leq x_{in} \leq \infty \quad H_1 \text{ is said to be declared} \end{cases}
\]

Sensors having their threshold \( \tau \) exceeded will indicate presence of an event. Further Fusion center needs to combine information from all of these sensors. The optimal test statistic at fusion center expressed in terms of Log Likelihood Ratio test is given as follows [7]

\[
\log \Lambda_1 = \log \frac{\prod_{n=1}^{N} P(u_{i,n},u_{2,n},\cdots,u_{L,n} \mid H_1)}{\prod_{n=1}^{N} P(u_{i,n},u_{2,n},\cdots,u_{L,n} \mid H_0)}
\]

\[
P(u_{i,n},u_{2,n},\cdots,u_{L,n} \mid H_1), P(u_{i,n},u_{2,n},\cdots,u_{L,n} \mid H_0) \text{ joint probability mass function (pmf) of the sensor decisions under } H_1 \text{ and } H_0 \text{ respectively.}
\]

A. Fusion of Three Sensors

The sensor decisions \( u_i \)'s are found to be correlated at the fusion center since they are observing the same event. A two sensor design case is evaluated in [7], on the same lines three sensor fusion is further extended as follows [10]. Considering,

\[
P(u_{i,n},u_{2,n},u_{3,n} \mid H_i) = P_{pqr}
\]

where \( P_{pqr} \) is the true probability of detection in case of an event occurrence, where \( p, q \) and \( r \) denote sensor 1, 2 and 3 decisions.

\[
p = u_{i,n} = (0,1), q = u_{2,n} = (0,1), r = u_{3,n} = (0,1)
\]

And hence eight different fusion cases arise for three sensor case as illustrated below.

\[
pqr(u_{i,n},u_{2,n},u_{3,n}) = (000,001,\cdots,111)
\]

Equation (5) indicates joint sensor 1, sensor 2 and sensor 3 decisions observing absence and presence of an event respectively for hypothesis \( H_1 \). Similarly,

\[
P(u_{i,n},u_{2,n},u_{3,n} \mid H_0) = Q_{pqr}
\]

where \( Q_{pqr} \) indicates the probability of false alarm. \( P_{pqr} \) and \( Q_{pqr} \) are joint probability mass function (pmf) of the sensor decisions under hypothesis \( H_1 \) and \( H_0 \) respectively. Hence for three sensor case, the eight different set of probabilities obtained are \( P_{000},P_{001},\cdots,P_{111} \) under \( H_1 \) and \( Q_{000},Q_{001},\cdots,Q_{111} \) for \( H_0 \). Further fusion of information from these three sensors is required for arrival of global decision of event occurrence. The optimal fusion statistic for \( L \) number of sensors is expressed as

\[
\log \Lambda_1 = C^T \gamma(u) = \sum_{n=1}^{N} \sum_{k=1}^{2^L-1} C_i^T \gamma_k(u)
\]

where \( C \) is the weight vector and elements of \( \gamma(u) \) are given by Bahadur Lazarsfeld polynomials [7]. Hence, for 3 sensors case the optimal test statistic at fusion center results into as in [10]

\[
\log \Lambda_1 = C_1^T \sum_{n=1}^{N} u_{i,n} + C_2^T \sum_{n=1}^{N} u_{2,n} + C_3^T \sum_{n=1}^{N} u_{3,n} + C_4^T \sum_{n=1}^{N} u_{i,n}u_{2,n}u_{3,n}
\]

\[
C_1(\text{Sensor1}) = \log \left( \frac{P_{100}Q_{000}}{P_{000}Q_{100}} \right)
\]

\[
C_2(\text{Sensor2}) = \log \left( \frac{P_{010}Q_{000}}{P_{000}Q_{010}} \right)
\]

\[
C_3(\text{Sensor3}) = \log \left( \frac{P_{001}Q_{000}}{P_{000}Q_{001}} \right)
\]

\[
C_4(\text{Sensor1,2}) = \log \left( \frac{P_{001}P_{100}Q_{010}Q_{000}}{P_{010}P_{000}Q_{000}Q_{101}} \right)
\]
\[ C_5(\text{Sensor1,3}) = \log \left( \frac{P_{111}P_{100}P_{010}P_{001}}{P_{100}P_{010}P_{001}P_{000}} \right) \]  

(13)

\[ C_6(\text{Sensor2,3}) = \log \left( \frac{P_{010}P_{001}P_{101}P_{100}}{P_{101}P_{100}P_{001}P_{000}} \right) \]  

(14)

\[ C_7(\text{Sensor1,2,3}) = \]  

\[ \log \left( \frac{P_{111}P_{100}P_{010}P_{001}P_{101}P_{110}P_{100}P_{010}P_{001}}{P_{100}P_{010}P_{001}P_{000}P_{011}P_{010}P_{001}P_{000}P_{001}} \right) \]  

(15)

When decisions of all three sensors are conditionally independent terms \( C_4 \) to \( C_7 \) equals zero and (8) reduces to Chair-Varshney(CV) rule [7] as given below:

\[ \log \Lambda_2 = C_1 \sum_{n=1}^{N} u_{1n} + C_2 \sum_{n=1}^{N} u_{2n} + C_3 \sum_{n=1}^{N} u_{3n} \]  

(16)

Thus it is observed from (8) that when the sensor observations are found to be correlated fusion statistics depends on individual as well as combined sensor information. Stronger is the correlation between them larger will be the fusion statistics. Whereas for independent sensor observations (16) results into CV rule considering information only from individual sensors.

**B. Joint Distribution Evaluation using Copulas**

In the above sections determination of Fusion rule requires joint distribution of sensor observations under both the hypothesis. Copulas are introduced [7] for evaluation of joint probability distributions and are also a strong tool for modeling of linear as well as non-linear dependence.

- **Sklar’s Theorem[11]:**

Considering random variables \( x_1, x_2, \ldots, x_L \) with marginal distribution functions \( F_1, F_2, \ldots, F_L \) in \([-\infty, \infty]\). Then according to Sklar’s theorem [11,12] there exists a Copula \( C \) such that

\[ F(x_1, x_2, \ldots, x_L) = C(F_1(x_1), F_2(x_2), \ldots, F_L(x_L)) \]  

(17)

For continuous distribution joint probability density function (pdf) is obtained by differentiating both sides of (17),

\[ f(x_1, x_2, \ldots, x_L) = (f(x_1)c(F_1(x_1), F_2(x_2), \ldots, F_L(x_L)) \]  

(18)

where \( c \) is the copula density given by

\[ c(k) = \frac{\partial^n}{\partial k_1 \cdots \partial k_L} (C(k_1, \ldots, k_L)) \]  

(19)

where \( k = [k_1, \ldots, k_m]^T \) and \( k_i = F_i(x_i) \).

Different types of copula functions exist and are selected which suits particular application. Elliptical and Archimedian copulas are the most widely used among the different multivariate copula families. Copula \( C \) function can be calculated using standard multivariate functions.

Normal or Gaussian and Student-t copulas belong to Elliptical family of copulas which are represented as follows:

- **Normal or Gaussian copula:**

\[ C_{ij}^\text{G}(k) = \phi^i(k_i) \cdots \phi^j(k_m) \]  

(20)

\( \phi \) is the multivariate distribution, \( \Sigma \) denotes correlation matrix and \( \phi \) represents univariate normal distribution function.

- **Student-t Copula:**

\[ C_{ij}^t(k) = t_{ij}(t_{i1}^{-1}(k_1) \cdots t_{ij}^{-1}(k_m)) \]  

(21)

where \( t_{ij} \) is the multivariate student-t distribution with correlation matrix \( \Sigma \), \( u \) degrees of freedom and \( t_{ij} \) denotes the univariate student-\( t \) distribution.

**C. Copulas for Two Sensor Case**

Considering two dimensional representation for two sensor case as shown in Fig. 1, where \( X \) and \( Y \) axis with (0,1) represent sensor 1 and 2 decisions respectively. It is seen in Fig. 1 four different regions depict joint distributions (00,01,10,11) for two sensor case.

**Fig. 1. 2D representation of copula model**

Joint distribution of two sensors is evaluated as given in [6]:

\[ P_{00} / H_1 = C(1 - p_1, 1 - p_2) \]  

(22)

\[ P_{01} / H_1 = 1 - p_1 - C(1 - p_1, 1 - p_2) \]  

(23)

\[ P_{10} / H_1 = 1 - p_2 - C(1 - p_1, 1 - p_2) \]  

(24)

\[ P_{11} / H_1 = p_1 + p_2 - C(1 - p_1, 1 - p_2) - 1 \]  

(25)

Similarly joint probabilities \( Q_{00}, Q_{01}, Q_{10}, Q_{11} \) under hypothesis \( H_0 \) are evaluated in similar manner by
replacing \( p_i \) with \( q_i \), where \( p_1 \) and \( p_2 \) represents probability of detection and \( q_1 \) and \( q_2 \) are probability of false alarm.

D. Copulas for Three Sensors Case

There are eight different joint probability distribution cases for three sensors which are given in [13], [15]. Considering eight unit cubes in Fig. 2, three dimensional representations joint distribution using copula functions is evaluated as follows:

\[
P_{000}, P_{001}, \ldots, P_{111} \text{ are the eight joint probability distributions under } H_1 \text{ which are evaluated as below.}
\]

\[
P_{000} / H_1 = C(1 - p_1, 1 - p_2, 1 - p_3) \quad (26)
\]

\[
P_{001} / H_1 = C(1 - p_1, 1 - p_2) - C(1 - p_1, 1 - p_2, 1 - p_3) \quad (27)
\]

\[
P_{010} / H_1 = C(1 - p_1, 1 - p_3) - C(1 - p_1, 1 - p_2, 1 - p_3) \quad (28)
\]

\[
P_{011} / H_1 = 1 - p_1 - C(1 - p_1, 1 - p_2) - C(1 - p_1, 1 - p_3) + C(1 - p_1, 1 - p_2, 1 - p_3) \quad (29)
\]

\[
P_{100} / H_1 = C(1 - p_2, 1 - p_3) - C(1 - p_1, 1 - p_2, 1 - p_3) \quad (30)
\]

\[
P_{101} / H_1 = 1 - p_2 - C(1 - p_1, 1 - p_2) - C(1 - p_2, 1 - p_3) + C(1 - p_1, 1 - p_2, 1 - p_3) \quad (31)
\]

\[
P_{110} / H_1 = 1 - p_1 - C(1 - p_1, 1 - p_3) - C(1 - p_2, 1 - p_3) + C(1 - p_1, 1 - p_2, 1 - p_3) \quad (32)
\]

\[
P_{111} / H_1 = 1 - (1 - p_1) - (1 - p_2) - (1 - p_3) + C(1 - p_1, 1 - p_2) + C(1 - p_2, 1 - p_3) + C(1 - p_1, 1 - p_3) - C(1 - p_1, 1 - p_2, 1 - p_3) \quad (33)
\]

Further for hypothesis \( H_0 \) probabilities \( Q_{000}, Q_{001}, \ldots, Q_{111} \) are evaluated replacing \( p_i \) by \( q_i \) using (41) and (42). \( p_1, p_2, \) and \( p_3 \) denotes probability of detection for sensor 1 ,sensor 2 and sensor 3 respectively while \( q_1, q_2, \) and \( q_3 \) are probability of false alarm.

![Fig. 2. 3D representation of copula model [12]](image)

III. RESULTS & DISCUSSIONS

Considering the illustrative example in [6], deploying a network of three sensors for detection of a nuclear radioactive source. The observations made under both hypotheses are

\[
H_0: \quad x_m = r_m^0 + b_m \quad (34)
\]

\[
H_1: \quad x_m = r_m^1 + b_m \quad (35)
\]

Radiation sensors receive radiation counts \( r_m^0 \) and \( r_m^1 \) in presence of background additive Gaussian noise \( b_m \) with known variance \( \sigma_w^2 \). Hence under both hypotheses sensor observations are found to be correlated due to common background noise. Also assuming the radiation counts follow Poisson distribution with known rate \( \lambda_b \) for background noise and \( \lambda_{ci} \) function of source intensity \( A_0 \) located at \( (x_0, y_0) \) is given by,

\[
\lambda_{ci} = \frac{A_0}{(x_0 - x_i)^2 + (y_0 - y_i)^2} \quad (36)
\]

Further marginal probability density functions (pdfs) of sensor observations under both hypotheses at any time instant are infinite Gaussian mixtures given as in [6]:

\[
f(x_m / H_0) = \sum_{k=0}^{\infty} \frac{a_k}{2 \pi \sigma_w} \exp \left[ - \frac{(x_m - k)^2}{2 \sigma_w^2} \right] \quad (37)
\]

\[
f(x_m / H_1) = \sum_{k=0}^{\infty} \frac{b_k}{2 \pi \sigma_w} \exp \left[ - \frac{(x_m - k)^2}{2 \sigma_w^2} \right] \quad (38)
\]

where

\[
a_k = \frac{\exp(-\lambda_b \lambda_{ci}^k)}{k!} \quad (39)
\]

And

\[
b_k = \frac{\exp(-\lambda_b^k \lambda_{ci}^k) \lambda_b^k}{k!} \quad (40)
\]

For all \( k = 0, 1, 2, \ldots \)

From the individual sensor pdfs further probability of detection \( p_i \) and false alarm \( q_i \) for \( i = 1, 2, 3 \) can be evaluated as

\[
p_i = \int_{-\infty}^{x_i} f(x_m / H_1) = \sum_{k=1}^{\infty} b_k Q \left( \frac{t_i - k}{\sigma_w} \right) \quad (41)
\]

\[
q_i = \int_{-\infty}^{x_i} f(x_m / H_0) = \sum_{k=1}^{\infty} a_k Q \left( \frac{t_i - k}{\sigma_w} \right) \quad (42)
\]

E. Determination of Fusion Center Threshold

The joint distributions could be further used for evaluations of Log Likelihood Ratio tests from (8). Numerical value of this equation is calculated and compared with the threshold of fusion center.
\[ \log \Lambda_i \leq \gamma' \]  

\( \gamma' \) is the threshold considered at fusion center. The likelihood ratio above threshold declares presence of an event otherwise event absence. The threshold can be further determined from [7,13], the probability of detection \( P_D \) and probability of false alarm \( P_{FA} \) of the system which are given as below:

\[ P_{FA} = Q \left( \frac{\gamma' - \mu_0}{\sigma_0} \right) \]  

\[ P_{DB} = Q \left( \frac{\gamma' - \mu_1}{\sigma_1} \right) \]  

where \( \mu_0, \sigma_0^2 \) = mean and variance under \( H_0 \)  
\( \mu_1, \sigma_1^2 \) = mean and variance under \( H_1 \) are derived in [14]. \( Q(.) \) is the complementary cdf of Gaussian distribution.

**F. Analysis of Three Sensor Case**

Considering the case of known copula parameters, i.e. correlation between the sensors \( \rho_0 \) and \( \rho_1 \) under hypothesis \( H_0 \) and \( H_1 \) respectively are known. Source intensity \( A_0 = 10 \), \( \lambda_0 = 0.625 \) and \( \lambda_1 = 10 \), with degrees of freedom \( \nu = 3 \). Assuming sensors are observing an event over \( N = 200 \) and \( 500 \) time intervals respectively. By varying \( P_{FA} \) the maximum achievable \( P_D \) is determined for Gaussian, Student-t copula and Chair-Varshney rule. As depicted from Fig. 3 and Fig. 4, observing an event repeatedly for \( N = 200 \) and \( 500 \) number of observations illustrates that probability of detection increases with more number of events detected. Also Copula based fusion Gaussian [14] and Student- t rules dominate Chair-Varshney rule in terms of higher probability of detection and hence system performance improves. It clearly represents that Copulas take into consideration dependency effect of sensors.

In absence of an event, sensors are still found to be spatially correlated due to background noise. Fig. 5, illustrates this case where the performance is evaluated for higher value of \( \rho_0 \) as compared to \( \rho_1 \). Higher value of \( \rho_0 \) results due to presence of additive Gaussian noise even in absence of an event. And hence all the fusion rules have almost same system performance due to sensors correlation of noisy data.

Fig. 3. Comparison of gaussian, Student-t, CV rule for N=200 observations

Fig. 4. Comparison of Gaussian, Student-t, CV rule for N=500 observations

Fig. 5. System performance in absence of an event with higher \( \rho_0 \)

Fig. 6. System performance in absence of an event with higher \( \rho_1 \)

Fig. 6 shows the system response in presence of an event where sensor observations are bound to be correlated with a higher a value of \( \rho_1 \). It is observed that CV rule has a lowest performance which considers only independent observations. Gaussian and Student-t Copula outperforms significantly in terms of higher probability of detection as compared to CV rule.
IV. CONCLUSIONS

This paper tried to model linear and non-linear dependencies using Copulas. A generalized fusion rule is proposed using Copulas for distributed detection of dependent sensor observations. The novelty of the 3D model developed lies in tri-variate analysis based on the existing 2D representation. Simulation results illustrate an improvement in detection probability with more number of event observations. Also it is observed that with increase in correlated observations, Gaussian and Student-t Copula has a superior performance as depicted in results. The results reveal that Copula based fusion rules, Gaussian and Student-t Copulas compared to Chair-Varshney rule for independent observations are outstanding. Future work will include a 4D Copula model and its behavioral study for higher dimensional multi-variables.

APPENDIX A GENERALIZED CASE FOR OBTAINING WEIGHT VECTOR $C$

Sensor weights are defined by $C_k$ and for $k = 1$ to $L C_1$ can be obtained as follows:

$$C_k(i, j, r) = \log \left( \frac{P_{U_1 \ldots U_i \ldots U_j \ldots U_r \ldots U_L} \cdot Q_{U_1 \ldots U_i \ldots U_j \ldots U_r \ldots U_L} \cdot \ldots \cdot Q_{U_1 \ldots U_i \ldots U_j \ldots U_r \ldots U_L}}{P_{U_1 \ldots U_k \ldots U_L} \cdot Q_{U_1 \ldots U_k \ldots U_L} \cdot \ldots \cdot Q_{U_1 \ldots U_k \ldots U_L} \cdot \ldots \cdot Q_{U_1 \ldots U_k \ldots U_L} \cdot 0 \ldots 0(Limes)} \right)$$

where

$u_L = 1$ for $L = i, \text{else} 0$,

$u_L = 1$ for $L = j, \text{else} 0$

$u_L = 1$ for $L = r, \text{else} 0$

$u_L = u_L + u_L' + u_L''$

And $a_L = u_L + u_L'$

$a_L = u_L + u_L''$

$a_L = u_L + u_L''$

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