Mitigation of Toxicity in Marine Musscls by Autonomous Mobile Agents

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Abstract - **We propose an autonomous algorithm for mobile agents in multisensor fusion. Our algorithm is based on the concept of mutual information (MI) and the bounds obtained for correlated information. The bounds are obtained by our technique of Determinant Inequalities to maximize the mutual information to achieve the conditions for autonomy. We demonstrate the superiority our autonomous algorithm over the Principal Component Analysis (PCA) in mitigating the trace element toxicity present in marine mussels.**

***Keywords*-mobile agents, autonomous systems, maximum mutual information, Determinant Inequalities, lower bounds.**

I. INTRODUCTION

The growing need to monitor natural resources in real time at a variety of scales has led to the development of automated devices such as the environmental sensor networks [1]. Deployment of large scale sensor network for marine application require long monitoring time and high frequency acquisition as the networks are flooded with large amount of measured data. In such a situation, analysis of local sensory data by the deployment of distributed sensor networks (DSNs) allows processed data to reach the base station (BS) without any loss as compared to data compression. Recently, Mobile Agents (MA) has replaced the traditional client/server model (CS) for data fusion due to greater stability, reduced network bandwidth, fault tolerant performance, robustness and reduction of work load [2, 3]. MA is a special kind of software which can execute autonomously. In MA computing model, data stay at the local site, while the processing task is moved to the data sites. Thus, blending MA with the DSNs to monitor environmental pollution is increasingly becoming popular [4, 5]. Since, all the decisions are made based on the available local information, we expect our MA to be self organized.

In this paper, we propose the use of MA as an inexpensive autonomous tool for the mitigation of TE toxicity. We use the correlation information in concentration between the TE to develop an algorithm for MA based on the concept of autonomy and information theory [6]. The technique of determinant Inequalities (DI) developed by us [7] enables us to estimate the bounds for these correlated information. Using the concept of mutual information (MI) and the bounds obtained, our algorithm establishes the conditions for autonomy. We demonstrate the superiority our autonomous algorithm over the Principal Component Analysis (PCA) in mitigating the trace element toxicity.

II. MATERIAL AND METHODS

A. *Autonomy*

Autonomous systems exhibit self determination and have the capacity to do independently according to self determined principle without being forced to do so by some outside power. Autonomous systems (the system in question may be a whole organism or a subsystem such as a neural network or metabolic cycle or a computer model of either of these) produce their own governance and use this self organizing process to modify its basic internal functions to enhance its survival viability. But, autonomy is not isolation, but does involve a significant degree of independence from outside influence. The concept of autonomy is widely being used in systems biology [8] and the recent focus is to design intelligent artificial agents mimicking autonomous capacity [9] in the field of artificial life.

B. *Information Theory Criteria for Autonomy*

In our computational model of autonomy, let X and Y be the two systems in an environment Z. Then in the information theory parlance, to be autonomous, the information theory criteria to be satisfied is [10]

$$I(X;Y|Z) > 0 \tag{1}$$

Hence, for the MA, to be autonomous, we should study the interaction between the systems X any Y due to correlation caused by the environment Z so that conditional MI in (1) is maximum.

According to the information theory [6] the mutual information I between any two systems is expressed by

$$I(X,Y) = H(X) + H(Y) - H(X,Y) = \text{Constant. Log. } G\rho \tag{2}$$

where Gρ is the determinant of the correlation matrix ρ. MI is a measure of statistical correlation between the systems X and Y whose value depends on the value of the determinant of the correlation matrix ρ. In order to maximize the MI, Gρ has to be maximized. Thus, by maximizing Gρ by the knowledge of the bounds for the correlated elements of ρ, the linear association or the correlated information between the systems is minimized. Minimization of the correlated information leads to systems being heterogeneous resulting in statistical independence. Hence, an index of independence or autonomy between two correlated systems is the maximization of the MI, by the estimation of upper and lower bounds for the correlated elements of the correlation matrix ρ. The algorithm developed by us to determine the upper and lower bounds of the correlation matrix by the technique of Determinant inequalities (DI) is described below.

C. Technique of Determinant Inequalities

Consider a quantity q, which is unknown or is difficult to estimate. A rigorous estimate of it, is provided by the upper and lower bounds, say U and L respectively, such that $U \geq q \geq L$. The unknown quantity q in our case is the constant concentration of trace element in the sea which causes correlation or bias. This constant bias appears in one or several elements of the determinant G. Let us suppose the sign of the determinant G can be determined. Then G can be considered as a polynomial in q i.e. G=G(q) and the roots of the determinant function G(q)=0 enable us to estimate the permissible values of q and hence the upper and lower bounds can be determined. Thus to determine the bounds on ρ

(a) The sign of the determinant G has to be known and

(b) The roots of the polynomial G(q)=0 should be determined.

The determinant G is positive when $\rho_{ij}= 0$. In this case, only the uncorrelated diagonal elements of ρ exist. Similarly the determinant G is zero when ρ_{ij} is either +1 or -1. Such a determinant is called a Gram determinant or Gramian and its positivity is expressed as an inequality

$$G \geq 0 \tag{3}$$

The upper and lower bounds are determined by solving the polynomial equation G(q) = 0.

D. Autonomous Algorithm

Let us designate the determinant as

G_i: with ith row and column deleted,
G_{ij}: with ith and jth row and column deleted, (note that when G has only two rows and columns then G_{12}=1)

g_{ii} :with $\rho_{ii} = 0$,
g_{ij} :with $\rho_{ij} = 0$, and row j and column i deleted.

According to (3), $G \geq 0$ and hence G_i and G_{ij} are also Gram determinants of lower order. Thus $G\geq0$, $G_i>0$, $G_{ij}>0$ and we can establish the following inequalities

$\rho_{ij} + (g_{ii} / G_i) \geq 0$,
$(g_+ - \rho_{ij}) (\rho_{ij} - g_-) \geq 0$

where $g_{\pm} =\{(-1)^{i+j}\, g_{ij} \pm (G_iG_j)^{0.5} \} / G_{ij}$

Thus for the uncorrelated component, the lower bound is

$$\rho_{ii} \geq - g_{ii} / G_i \tag{4}$$

While, for correlated component the upper and lower bounds are

$$G_+ \geq \rho_{ij} \geq g_- \tag{5}$$

III. Results

Among the ten trace elements in the marine mussels, we focused our attention on Cr whose excessive intake leads to breast cancer. The upper and lower bounds for the concentration of nine elements which has correlation with Cr are obtained using (5). The lower bound of each of these elements which maximizes the MI according to the autonomous criteria of (1) is depicted in Table 1 along with the values of ρ obtained by the PCA.

TABLE 1. COMPARISON OF ρ FOR CR OBTAINED BY THE TECHNIQUE OF DETERMINANT INEQUALITIES (DI) AND THE PRINCIPAL COMPONENT ANALYSIS (PCA)

No.	Element	Existing Value of ρ of Cr with other TE	Lower bound values of ρ by DI	PCA values
1.	Al	0.85	0.69	0.94
2.	Mn	0.80	0.67	0.91
3.	Fe	0.83	0.67	0.89
4.	Co	0.31	0.04	0.36
5.	Ni	0.28	-0.01	0.28
6.	Cu	-0.08	-0.31	-0.11
7.	Zn	0.73	0.56	0.82
8.	Cd	0.87	0.64	0.92
9.	Pb	0.72	0.57	0.83

IV. Discussion

Minimization of the correlated information leads to systems being heterogeneous resulting in statistical independence. From Table 1, it is apparent that lower bound values obtained by our technique of DI are the least as compared to both the existing values as well as those obtained by PCA. Thus, by autonomous criteria, selective mitigation of toxicity of a specific trace element is possible by decreasing its association in concentration with the other trace elements. The technique of DI enabled, to obtain the bounds for each of the trace element so that association with the other elements can be selectively decreased by employing maximization of MI. Such element wise mitigation is possible only by our autonomous criteria and not by either the PCA or Independent Component Analysis (ICA). PCA, ICA and the Factor Analysis (FA) create independence in attribute dependence by linear transformation. These methods even though work in multivariate environment, target only bivariate dependence and linear feature dependencies and hence are not sufficient to eliminate all dependencies in the data [11]. The concept of autonomy is based on conditional dependencies and algorithms based on it lead to improved computational performance [12]. Further, as the mutual information is shared exclusively by the involved attributes, autonomous criteria is stable and unambiguous as adding any new attribute will not change the existing interaction.

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