

## Fault Diagnostic of Variance Shifts in Clinical Monitoring Using an Artificial Neural Network Input Gain Measurement Approximation (ANNIGMA)

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### Abstract

Condition of a patient in an intensive care unit is assessed by monitoring multiple correlated variables with individual observations. Individual monitoring of variables leads to misdiagnosis. Therefore, variability of the correlated variables needs to be monitored simultaneously by deploying a multivariate control chart. Once the shift from the accepted range is detected, it is vital to identify the variables that are responsible for the variance shift detected by the chart. This will aid the medical practitioners to take the appropriate medical intervention to adjust the condition of the patient. In this paper, Multivariate Exponentially Weighted Moving Variance chart has been used as the variance shift identifier. Once the shift is detected, authors for the first time have used ANNIGMA to identify the variables responsible for variance shifts in the condition of the patient and rank the responsible variables in terms of the percentage of their contribution to the variance shift. The performance of the proposed ANNIGMA has been measured by computing average classification accuracy. A case study based on real data collected from ICU unit shows that ANNIGMA not only improve the diagnosis but also speed up the variable identification for the purpose of appropriate medical diagnosis.

### Keywords

MEWMV chart · Neural networks · Clinical monitoring · Univariate moving range char · Multivariate variability

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### 40.1 Introduction

Patients are placed in an intensive care unit (ICU) following major surgery. Continuous monitoring is essential to the daily care of ICU patients. Ongoing and continuous monitoring is achieved by complex devices that require special training and experience to operate. If certain physiologic limits are exceeded, the devices set to generate alarms. Those alarms need to be investigated by following strict protocols. The measured observations are highly correlated for a given patient and the condition of the patient is assessed with individual observations. It is imperative to maintain overall variability of all the observations with respect to the accepted variability (target variance-covariance matrix) in order to achieve stable medical condition for the patient.

In this paper, Multivariate Exponentially Weighted Moving Variance (MEWMV) chart [1] has been used as the variance shift identifier for individual observations. The advantage of MEWMV chart is its ability to monitor variance while stabilizing mean of the process. The challenge in deploying multivariate control chart [2] is to identify variables responsible for the out-of-control (OOC) signals (fault diagnoses). Several machine learning approaches such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) have been proposed [3–12] for fault diagnoses. Hsu et al. [13] proposed an improved artificial neural networks called ANNIGMA approach. The method incorporates weights analysis based heuristic to direct the search in the wrapper model and allows effective feature selection for ANN.

This paper for the first time presents new strategy for fault diagnosis of variance shifts in multivariate clinical processes. The proposed approach integrates the deployment of MEWMV chart with ANNIGMA.

### 40.2 MEWMV Chart

MEWMV chart has the ability to monitor multivariate process variability while stabilizing the mean. Huwang et al. [1] has introduced the chart by estimating optimal control limits for up to 3 variables. Gunaratne et al. [14] have extended the charts ability to monitor high dimension multivariate processes by estimating control limits for up to 15 variables and introducing a mathematical model to estimate control limits beyond 15 variables.

Let  $a = (a_1, \dots, a_p)^T$  be a random vector that represents  $p$  correlated quality characteristics from a multivariate process. Consider a transformation of  $a$ ,  $X = \sum_0^{-1/2} (a - \mu_0)$  such that  $X$  is distributed as  $N(\mu, \Sigma)$ , where  $\mu = \sum_0^{-1/2} (\mu - \mu_0)$  and  $\Sigma = \sum_0^{-1/2} \sum u \sum_0^{-1/2}$ . Consequently, when the process is in-control,  $X$  is distributed as  $N(0, I_p)$ , where  $I_p$  is  $p \times p$  identity matrix.

The MEWMV statistic  $V_t$  [1] is defined by

$$V_t = \omega (X_t - Y_t) (X_t - Y_t)' + (1 - \omega) V_{t-1} \quad (40.1)$$

Where  $Y_t$  is the predicted mean shift at sampling point  $t$  and its value is obtained by the multivariate exponentially moving average of  $X_t$

$$Y_t = \lambda X_t + (1 - \lambda) Y_{t-1} \quad (40.2)$$

They have shown that for  $0 < \omega < 1$ ,  $0 < \lambda < 1$  and  $t \leq p$ , the matrix  $V_t$  is positive definite with probability 1.

Defining  $I_t$  as the  $t \times t$  identity matrix and  $X, Y, D$  and  $N$  as follows

$$X_t = (X_1, X_2, \dots, X_t)'$$

$$Y_t = (Y_1, Y_2, \dots, Y_t)'$$

$$D = \text{diag} (D_1, D_2, \dots, D_t)$$

$$N = \begin{pmatrix} \lambda & 0 & \dots & 0 \\ \lambda(1-\lambda) & \lambda & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \lambda(1-\lambda)^{t-1} & \dots & \lambda(1-\lambda) & \lambda \end{pmatrix}$$

Huwang et al. [1] showed that  $V_t$  can be written as

$$V_t = (X - Y)' D (X - Y)$$

$$= X'(I_t - N)' D (I_t - N) X$$

$$V_t = X' R X$$

$$E [tr (V_t)] = p^* tr (R) \quad (40.3)$$

$$\text{Var} [tr (V_t)] = 2 p \sum_{i=1}^t \sum_{j=1}^t r_{ij}^2 \quad (40.4)$$

Therefore, the control limits for MEWMV chart are given by

$$\begin{aligned} E [tr (V_t)] &\pm L \sqrt{\text{Var} [tr (V_t)]} \\ &= p tr (R) \pm L \sqrt{2 p \sum_{i=1}^t \sum_{j=1}^t r_{ij}^2} \end{aligned} \quad (40.5)$$

The constant  $L$  depends on  $p, \omega$  and  $\lambda$ . The value of  $L$  can be estimated by time consuming Monte Carlo simulations [15]. However, Gunaratne et al. [14] have developed predictive models to obtain the control limits for any high dimension multivariate process.

### 40.3 Annigma Approach

Hsu et al. [13] proposed a weights analysis based wrapper heuristic called ANNIGMA. It is a feature ranking approach which is mathematically derived from the back propagation training formulation of ANN. ANNIGMA also ranks the quality characteristics by the relevance which is based on the weight associated with the quality characteristic in a neural network based wrapper approach. Therefore, it is not necessary to train  $m$  neural nets for each branching point. Consequently, the speed of the fault diagnostic task using ANNIGMA would substantially increase.

For a two-layer neural network, if  $i, j$  and  $k$  are the input, hidden and output layer and  $F$  is a logistic activation linear function  $F(x) = 1/(1 + \exp(-x))$  then output of the network is given by Eq. (40.6).

$$O_k = \sum_j F \left( \sum_i A_i \times W_{ij} \right) \times W_{jk} \quad (40.6)$$

where  $W_{ij}$  and  $W_{jk}$  are the network weights. The local gain can be defined as:

$$LG_{ik} = \left| \frac{\Delta O_k}{\Delta A_i} \right| \quad (40.7)$$

According to [13], the local gain  $LG_{ik}$  can be defined in terms of network weights by

$$LG_{ik} = \sum_j |W_{ij} \times W_{jk}| \quad (40.8)$$

The ANNIGMA score for  $i$ th input and  $k$ th node is defined as [13]

$$ANNIGMA_{ik} = \frac{LG_{ik}}{\max(LG_k)} \quad (40.9)$$

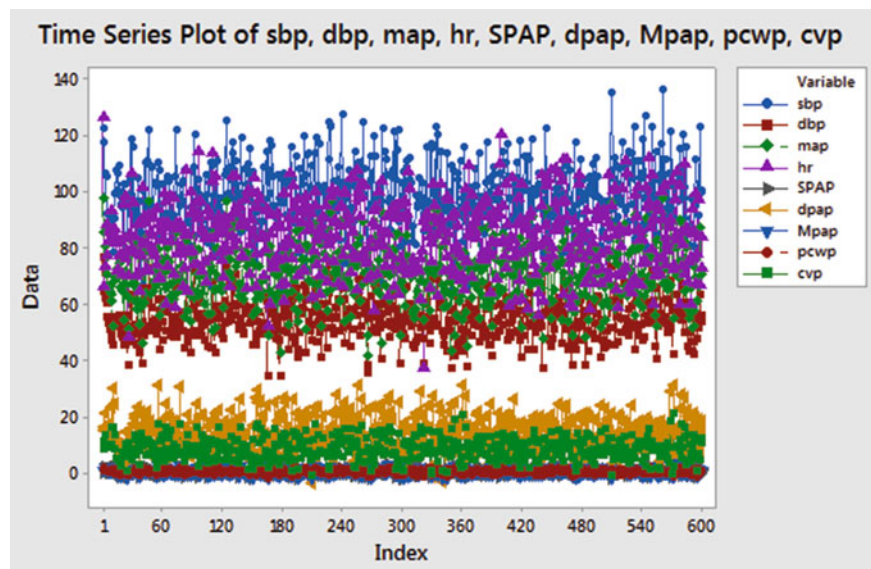
Neural Network weights give an estimate of the relative importance of input features.

#### 40.4 Case Study: Application of the Proposed Approach in Monitoring ICU Patients

Authors have used observations from 9 correlated variables that play a substantial role in assessing the condition of a patient after open heart surgery. This is usually achieved by screening Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Mean Arterial Pressure (MAP), Systolic Pulmonary Artery Pressure (SPAP), Diastolic Pulmonary Artery Pressure (DPAP), Mean Pulmonary Artery Pressure (MPAP), Pulmonary Capillary Wedge Pressure (PCWP), Central Venous Pressure (CVP) and Heart Rate (HR). The characteristics indicate highly significant correlation (P-value = 0.05) among them. A total of 600 samples of size one with 9 characteristics in each sample were available. The data recording times were recommended by the medical practitioners. The study has used all the collected data.

The Time Series plots for 9 variables (Fig. 40.1) suggest that the most independent variables are CVP, DPAP and MAP. The Correlation analysis also confirms this.

**Fig. 40.1** Time series plot for 9 variables



#### 40.4.1 MEWMV Chart for Monitoring the Variability of the Condition of a Patient After Heart Surgery

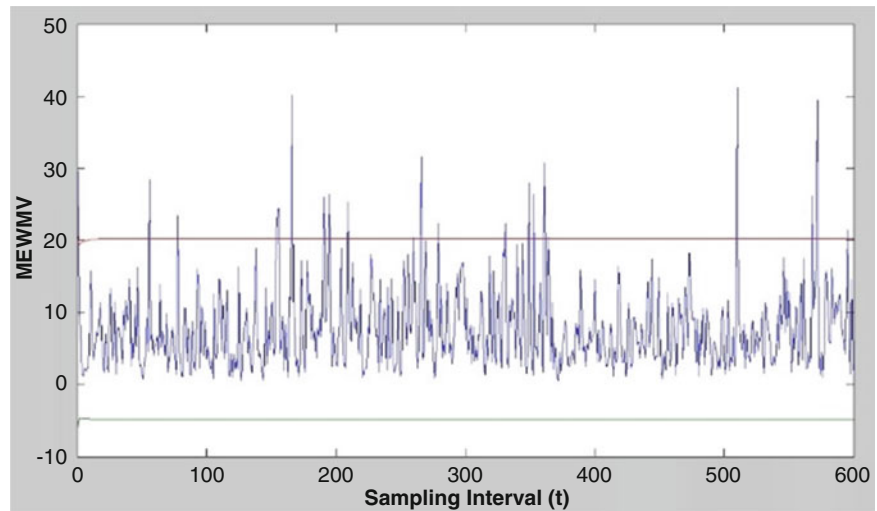
MEWMV chart has been used to monitor large variance shifts ( $\omega = 0.9$ ) while mean is stabilized for small shift ( $\lambda = 0.1$ ). Stabilizing mean is essential while monitoring variance of the process to avoid capturing mean changes. The control limits for the MEWMV charts are obtained using the predictive models developed by Gunaratne et al. [14]. Figure 40.2 shows 22 OOCs for MEWMV chart (out of 600 observations).

#### 40.4.2 Fault Diagnostics to Identify the Responsible Characteristics Based on ANNIGMA Approach

The OOCs and in-control samples from MEWMV chart have been injected to ANNIGMA and other commonly used machine learning approaches to identify the group of variables responsible for in-controls and OOC signals and estimate the percentage of their individual contribution to the signals. The accuracy of ANNIGMA results have been investigated by deploying univariate Moving Range (UMR) charts.

Table 40.1 shows the ANNIGMA approach is superior to other commonly used approaches in selecting the minimum number of variables with higher accuracy. The accuracy computation starts with full variables set. The lowest ranked variable has been removed by utilizing Backward Elimination (BE) process. BE iteration continues until last variable in the subset. The subset with highest accuracy with minimum number of variables has been selected as the best subset. The

**Fig. 40.2** Out-of-controls for MEWMV chart



**Table 40.1** Average accuracies for large variance shifts ( $\omega = 0.9$ ) while mean is stabilized for small shifts ( $\lambda = 0.1$ )

Number of variables	ANNIGMA accuracy	Maximum relevance filter	SVM	Naïve-Bayes
9	96.53	96.58	96.33	94.83
8	96.96	96.58	96.33	94.83
7	96.43	96.16	96.33	96.00
6	96.26	<b>96.66</b>	96.33	96.16
5	96.53	95.66	96.33	96.66
4	96.60	95.83	96.33	<b>97.50</b>
<b>3</b>	<b>97.00</b>	95.83	96.33	97.33
2	96.53	95.91	96.33	96.83
1	96.86	96.33	96.33	96.83

**Table 40.2** Percentage contribution of variables selected by ANNIGMA to fault signals

Variable name	% Contribution
MAP	37.96%
DPAP	31.99%
CVP	30.05%

highest accuracy (97%) achieved for ANNIGMA by monitoring only 3 characteristics, i.e., 97% of the total variability of the patient condition is due to Mean Arterial Pressure (MAP), Diastolic Pulmonary Artery Pressure (DPAP) and Central Venous Pressure (CVP).

ANNIGMA also ranked the percentage contribution of the significant variables as shown in Table 40.2. The highest contributing variable for the OOC signals is MAP (37.96%) followed by DPAP (31.99%) and CVP (30.05%).

## 40.5 Fault Diagnosis Using Univariate Moving Range (UMR) Charts

Traditional statistical approach for identifying variables responsible for the variance shift in multivariate chart is to deploy UMR charts for each individual variable and select the variables that produce OOC signals similar to MEWMV chart. However, this approach disregards the correlation among variables and may misdiagnosis the cause of the OOC signals (samples that are in control in multivariate chart may be OOC in UMR charts or vice versa).

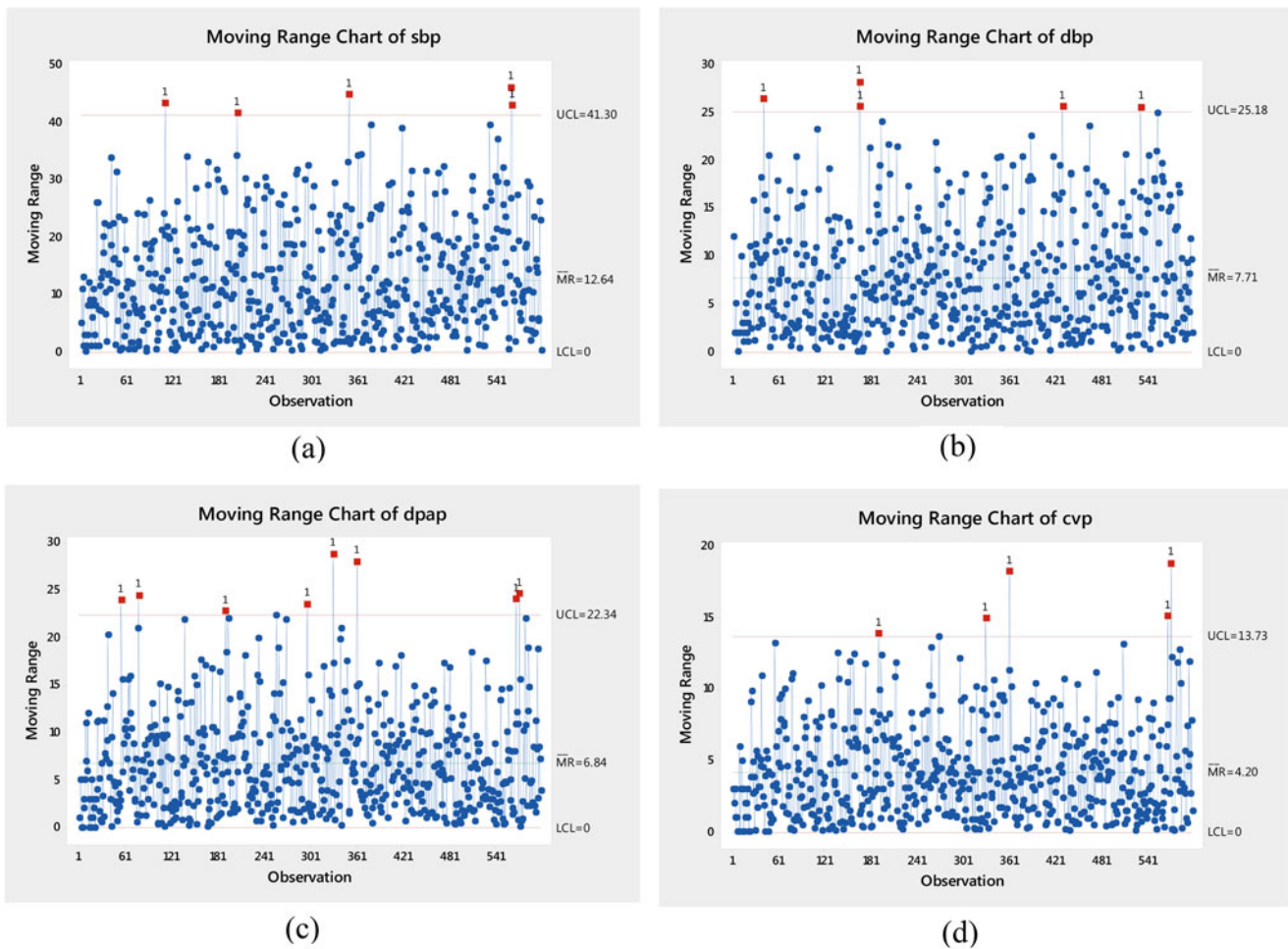
UMR charts for SBP, DBP (Fig. 40.3a, b) and HR do not produce any OOC observations that matches OCCs produced by MEWMV chart. ANNIGMA removes SBP, DBP and HR variables as insignificant variables to process faults at early stage. The following UMR charts (Fig. 40.3c, d) show OOC signals for two of the responsible variables DPAP and CVP which have been identified by ANNIGMA. The OOC signals almost match those produced by the MEWMV chart.

Accuracy has been calculated for the variables selected by ANNIGMA (MAP, DPAP and CVP) using UMR charts. Table 40.3 shows the calculated accuracies are approximately close to 97% as indicated by ANNIGMA. Percentage contribution (around 33%) also in line with the ANNIGMA results. Therefore, UMR charts results further confirm the precision of results given by ANNIGMA.

## 40.6 Conclusion

Fault diagnostic in multivariate control chart can be performed either by deploying univariate control chart for each individual characteristics or deploying machine learning ap-





**Fig. 40.3** UMR charts. (a) UMR charts for SBP (b) UMR charts for DBP (c) UMR charts show OOC signals for DPAP (d) UMR charts show OOC signals for CVP

**Table 40.3** Accuracy and percentage contribution based on UMR charts

	MAP	DPAP	CVP
OOcs in MEWMV	22	22	22
OOcs in UMR	3	8	5
matching OOcs with UMR	1	5	4
matching in-controls with UMR	576	575	577
Accuracy for UMR (%)	96.1	96.6	96.8
Percentage contribution (%)	33.2	33.4	33.4

proaches such as ANNs, SVMs and ANNIGMA. However, univariate charts not only ignore the correlation among the variables but also are time consuming as the number of variables to be monitored increases. This paper for the first time deployed ANNIGMA to identify and rank the characteristics responsible for the multivariate variance shifts when monitoring ICU patients. Average classification accuracy has been used to select the most significant subset of variables. The comparison results show that ANNIGMA approach

select the responsible variables more effectively than other commonly used machine learning approaches. Information on the extent of the responsible variables' abnormal rates and rhythms to the patient condition can effectively aid the medical practitioners in their early diagnostics intervention tasks.

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