Diagnostic Monitoring of Industrial Robots

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Abstract

With greater integration of industrial robots into factories and manufacturing processes, failures have the potential to significantly disrupt production and cause injury. There is an urgent need for methodologies that can be used to develop systems for dynamic monitoring and diagnosis of factory machines. In this research, we use four time-series based pattern recognition methods for diagnostic monitoring to develop a multi-attribute assessment method for monitoring abrupt changes in operating conditions of industrial robots.

Introduction

Industrial robots provide important capabilities for increasing the productivity of modern manufacturing. While robot dynamics and control have been extensively studied over the past two decades [1], failures can cause catastrophic effects to production and sometimes result in serious injuries to the work force. In order to control the path of a robot, encoders or resolvers at the axes provide a means for dynamic feedback of positional information so that proper control actions can be determined in real-time. On the other hand, sensor based monitoring to predict and diagnose failures is not provided with commercially available robots. Potential malfunctions of robotic machines should be closely monitored and evaluated so that scheduled maintenance can be implemented before a breakdown occurs. In this research, an industrial robot is used to evaluate some candidate methods for dynamic monitoring and diagnosis.

Monitoring and diagnosis techniques have been successfully used for fault detection of machines and manufacturing systems [2, 3]. In contrast to machine tool cutting processes or machine vibration, however, a significant portion of the events to be monitored in an industrial robot is the motion of multiple axes. A cycle of robot motion typically combines trajectories that have been programmed to achieve specific actions. Industrial robots often are operated at slower speeds when they carry a heavier load to improve repeatability. For these reasons this research investigates the use of approaches to perform dynamic monitoring and diagnostic functions needed for industrial robots. Possible motor and component failures of an IBM 7535 robot are analyzed using
time-series based multi-attribute assessment techniques. Experimental data are recorded and diagnosed to identify possible failure modes.

**Time Series Models**

The operation of an industrial robot is modeled as a stochastic process using the auto-regressive moving average (ARMA) method \([4,5]\). The output state of the process can be represented by

\[
X_t = \frac{C(B)}{d(B)} a_t = \sum_{k=1}^{\infty} \beta_k a_{t-k}
\]  

(1)

where \( \phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_n B^n \) denotes the auto-regressive (AR) operator, and \( C(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_m B^m \) denotes the moving average (MA) operator. \( B \) is the backshift operator defined by \( B a_t = x_{t-1} \), and \( \phi_1, \theta_1 \) are model coefficients to be specified. An ARMA model of the process can also approximated to a particular accuracy by the series

\[
X_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_n x_{t-n} + a_t
\]  

(2)

which can be expressed by the linear algebraic system

\[
X_t \psi = A_t
\]  

(3)

where \( \psi = \begin{bmatrix} 1, -\phi_1, -\phi_2, \cdots, -\phi_n \end{bmatrix}^T \) is the AR model parameter vector, \( A_t = \begin{bmatrix} a_{n+1}, a_{n+2}, \cdots, a_N \end{bmatrix}^T \) is a white noise time-series, and

\[
X_t = \begin{bmatrix}
    x_{n+1} & x_n & x_1 \\
    x_{n+2} & x_{n+1} & x_2 \\
    \cdots & \cdots & \cdots \\
    x_N & x_{N+1} & x_{N-n}
\end{bmatrix}
\]  

(4)

is a data matrix. The residual sum of squares can be expressed as

\[
\text{RSS} = A_t^T A_t = \psi^T R \psi, \quad \text{where} \quad R = X_t^T X_t.
\]  

(5)

**Pattern Recognition and Cluster Analysis**

Pattern recognition techniques can be used to classify phenomenon into labeled patterns. In practice, however, these patterns may not be precisely defined and the observation may not clearly fall into one of the existing patterns. In this situation, cluster analysis and multi-attribute assessment techniques are useful. In general, cluster analysis can be used to determine patterns of a system described by empirical data. Phenomena contained in a
region of feature space, where the pattern density is larger than that of surrounding regions, is called a cluster. Bayes decision theory and nearest neighbor classification rules are frequently used to determine the closeness of a cluster. In situations where an observation cannot be clearly classified, identification techniques have been proposed. We propose a procedure for multi-attribute assessment diagnosis based on the following four identification methods: improved Euclidean distance (ED), cross entropy minimization (CE), characteristic frequency and damping ratio analysis (CFDR), and normalized residual sum of squares (NRSS).

The improved euclidean distance method is based on a parametric measure of dissimilarity between the two time-series with distinct features [6]. The concept can be applied to fit an observation \( x_t \) of the system pattern by the distance function

\[
ED([\psi_t],[\psi_t]) = \sum (\phi_t - \phi_t)^2 = (\psi_t - \psi_t)^T W (\psi_t - \psi_t)
\]

where \( \psi_t \) is a model parameter vector and \( W \) is a weighting matrix chosen to adjust the sensitivity of the fit. Taking into account the variance of the samples, the weighting matrix can be expressed as \( W = R = X_t^T X_t \).

The cross entropy of two stochastic processes is a non-parametric measure of the dissimilarity between two sample observations (with probability densities \( P_1, P_2 \)) defined by [7]:

\[
CE(P_1, P_2) = \int P_1(\chi) \ln \frac{P_1(\chi)}{P_2(\chi)} d\chi
\]

Using the nearest neighbor approach, the test data can be classified into a reference pattern which has a minimum cross entropy with the test data. The decision error probability of such a classification can be estimated by

\[
\Gamma(e) = \int \Gamma(e/\chi) d\chi
\]

For the time-series treated above, the probability density associated with the model approximation is

\[
\Gamma(\chi) = \frac{1}{(2\pi)^{n/2} |\Lambda|^{1/2}} e^{-1/2 \chi^T \Lambda^{-1} \chi}
\]

where \( \Lambda \) is the expected value of the variance. Consequently the cross entropy of the test and reference time-series becomes
\[ \text{CE}(\psi_r, \psi_i) = \ln \frac{\sigma_t^2}{\sigma_r^2} + \frac{\sigma_{r,t}^2}{\sigma_r^2} - 1 \]  

(10)

where \( \sigma_t \) is the standard deviation of the data fitted into the model, \( \sigma_r \) is the standard deviation of the reference model (with a predefined pattern), and \( \sigma_{r,t} \) is the standard deviation of the test data fitted into the reference model.

In the localized characteristic frequency method we examine variations of characteristic frequencies and damping ratios of the system pattern. The characteristic equation of the auto-regressive portion of the time-series can be expressed as \([8]\):

\[ \lambda^n - \sum_{j=1}^{n} \phi_j \lambda^{n-j} = 0 \]  

(11)

The \( n \) solutions of the characteristic equation \( \omega_n \), \( i=1,...,n \) define the positions of the characteristic frequencies of the system. Each pair of complex roots represents a peak at the characteristic frequencies

\[ \omega_n = \frac{1}{\Delta} \sqrt{\frac{\ln \left| \lambda_i \lambda_i^* \right|^2}{4} - \left( \cos \frac{\lambda_i + \lambda_i^*}{2\sqrt{\lambda_i \lambda_i^*}} \right)^2} \]  

(12)

where \( n \) is the order of the AR part and \( \Delta \) is the sample interval. The damping ratio is

\[ \zeta_i = \sqrt{\frac{1}{\sqrt{\frac{\ln \left| \lambda_i \lambda_i^* \right|^2}{4} + 4 \left( \cos \frac{\lambda_i + \lambda_i^*}{2\sqrt{\lambda_i \lambda_i^*}} \right)^2}}} \]  

(13)

By comparing the locations of the characteristic frequencies of the normal system pattern with those in the observations, we can identify a change in system operation.

The variance of a system time-series is a measure of the total energy of the motion pattern. Changes in this quantity can be used to indicate abnormal operation of the system. As shown by Li et al. \([9]\) the variance can be expressed...
\[ \Omega(x_t) = E[(x_t - \bar{x}_t)^2] = \sigma^2_t \sum \sum g_i g_j \frac{1}{1 - \lambda_i \lambda_j} \quad (14) \]

where \( x_t \) is the test data, \( \bar{x}_t \) is the average of the test data,

\[
g_i = \frac{\prod_{k=1}^{m} (\lambda_i - \nu_k)}{\prod_{k=1, k \neq i}^{n} (\lambda_i - \lambda_k)} \quad (15)
\]

is the Green's function of the ARMA model, \( E \{ \cdot \} \) is the expectation operator, \( \lambda_i \) is the characteristic root in the auto-regressive part, \( \nu_k \) is the characteristic root in the moving average part, and \( \sigma^2_t \) is the variance of the noise.

Typically the approach is implemented using a generalized recursive least squares method in which the model is updated as the observations are obtained. The feature value \( \Omega(x_i) \) in the variance analysis combines the influence of the recursive least squares method and system features to indicate abnormalities in the system operation. The variance is normalized to minimize the effects of predictable factors such as variation of the machine load. The influence of variations in standard deviation can be obtained by examining the criterion

\[
NRSS = \sigma^2_t / \Omega(x_t) \quad (16)
\]

If a normal reference model pattern is obtained from measurement of the timeseries, the RSS will increase when the corresponding model parameters \( \Phi_i \) and \( \Theta_i \) are used to fit the measured data. In this approach the normalized residual sum of squares

\[
NRSS = \frac{\sum_{i=1}^{n} \sum_{i=1}^{n} \frac{R_i \cdot \bar{R_i}}{1 - \lambda_i \lambda_i}} \quad (17)
\]

can indicate deviations in the system operation [9].

**Multi-Attribute Assessment Technique**

The use of cluster analysis methods usually involves uncertainties in their application to specific situations. Methods based on fuzzy logic offer a convenient approach for describing ambiguous patterns. Between two extreme cases in which success and failure may be denoted by 1 and 0, respectively, there are many intermediate possibilities. When used in situations characterized by
imprecise or fuzzy information, the pattern recognition methods described above will result in a decision with a certain level of confidence. Application of different methods to the same situation may result in conflicting results because of the uncertainties associated with each method. To alleviate this difficulty, we will assign a membership function to each of the cluster methods and weight them to obtain a more reliable decision based on multi-attribute assessment evaluation. The membership functions can be defined through sensitivity analysis of each cluster method based on analysis of the data from the process being diagnosed.

A multi-attribute assessment vector is defined as \( U = [u_1, \ldots, u_n] \) and the state vector by \( V = [v_1, \ldots, v_m] \). The fuzzy membership matrix \( F = [f]_{n \times m} \) and a weighting vector \( \alpha = [\alpha_1, \ldots, \alpha_n] \) can be determined. Siskose et al. [10] show that the multi-attribute assessment function can be expressed as \( R = \alpha \bullet F \) where \( \bullet \) denotes an assessment operation such as minimum distance, maximum value, or a logical (AND/OR) operation. Results from this approach will provide an improved classification for identification of failures.

Diagnostic Monitoring of Industrial Robot Motion

An IBM 7535 industrial robot was programmed to perform a pick and place operation. Two DC servo motors drive the primary rotary axes, and a stepper motor drives the roll axis. The operational speed was programmed at three different levels to simulate motor malfunctions: \( S1 \) denotes a slow speed (heavy payload), \( S2 \) denotes a standard speed, and \( S3 \) denotes a fast speed (light payload). Deviations from the standard speed were considered to be abnormal motions. A pair of accelerometers were mounted on the last arm of the wrist. Data measured by the accelerometers were recorded and processed to determine the operating pattern variation using four time-series based methods and the multi-attribute assessment technique. Table 1 shows the AR model parameters for the three speeds.

The three motion patterns were tested and their time-series are shown in Figures 1a, 1b, and 1c, corresponding to speeds \( S1, S2, \) and \( S3 \), respectively. The high amplitude region represents the robot motion part and the low amplitude noise denotes a pause between the pick and place movements. As the operation speed increases the high amplitude region decreases.

These time histories were transformed into the frequency domain and their power spectra are shown in Figures 2a, 2b, 2c. To filter the data and thereby reduce the noise, we applied a time-series spectral method that resulted in a much smoother spectra. We observe that the peak shifts to the right when the operational speed increases. There are four frequency components in the robot motion patterns. The first mode (20-25 Hz) was related to the base oscillation. The second mode (45 Hz) resulted from the stepper motor on the roll axis. The
third mode was related to the DC servo motor that drives the second link. The fourth mode was an induced oscillation caused by a mechanical clearance ("defect") between the second link and the roll axis.

A ten-term AR model was constructed and applied to all three operating conditions of the industrial robot. The multi-attribute assessment technique was implemented using the four pattern recognition methods described above. Variations in patterns using these methods were compared. The Euclidean distance (ED) calculations for three robot operating conditions are summarized in Figure 3a. The cross entropy (CE), normalized residual sum of squares (NRSS), and characteristic frequency (CFDR) values were also computed and these results are summarized in Figures 3b, 3c, and 3d, respectively. All four methods show significant variations between the three operating speeds (payloads). Although characteristic frequencies for the three speeds were estimated, only the third frequency was sensitive to speed changes. ED, CE, and the characteristic frequency increase with increasing robot speed; NRSS decreases with increasing robot speed.

Based on the experimental results, a multi-attribute assessment vector is chosen as \( U = \{ \text{ED, CE, F3, NRSS} \} \) and the system state is represented by \( V = \{ S1, S2, S3 \} \) where \( S1, S2, \) and \( S3 \) denote the operation speeds of the robot as discussed in the preceding section, and \( F3 \) denotes the third frequency resulting from the characteristic frequency method. A new robot motion was recorded and a time-series model was constructed to provide a means for classifying the test motion into one of the three states defined by the state \( V \) using the multi-attribute assessment technique. Numerical values for ED and CE for the test motion were computed for the three system states. In addition, the third characteristic frequency and NRSS were computed. Details of the model and the results are shown in the Appendix.

The improved Euclidean distance method indicates the sample closest to \( S2 \) while the cross entropy method indicates the sample closest to \( S2 \). Using the results of Yu [11], membership functions for these two situations were chosen to be 0.8, and membership functions for the others were chosen to be 0.2. The frequency computation (F3), however, lies between \( S2 \) and \( S3 \). Therefore, membership functions are assigned in this case as 0.2, 0.5, and 0.5 for each of the three speeds.

Use of the NRSS method indicates that the sample is closer to \( S3 \) so that the membership functions are assigned to be 0.2, 0.3, and 0.7. Summing all of the membership functions with equal weights, the last column in Table 2 shows that the robot operation can be classified as \( S3 \). This resulting classification verifies the fact that the test motion was obtained based on \( S3 \). While a unit weighting factor was assigned to each pattern classification method, different weights can be chosen to denote importance or confidence in one or more methods.
Conclusions

A multi-attribute assessment technique based on four time-series identification methods has been proposed for dynamic diagnostic monitoring of industrial robot operation. These four methods were used to identify system characteristics and patterns of robot motions. We observed that all four methods can reasonably identify the motion characteristics and patterns of robot motion, however, the CE method showed the highest sensitivity and NRSS the lowest sensitivity to speed changes. Use of the multi-attribute assessment analysis provides an integration of pattern recognition methods to improve the classification. Specific membership functions for each method need to be incorporated to provide a more reliable classification. The experiments indicate that deviations from a standard reference pattern can be clearly identified and used to provide a warning prior to machine failure.

References

Appendix

The computed AR parameters for the experimental results corresponding to speed S3 are as follows:

$$\Psi = (-0.1222, -0.0855, 0.2313, 0.0145, 0.0855, 0.1771, 0.0905, 0.0093, 0.1253, 0.075)$$

$$\sigma_n = 0.8143$$

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>F3 = 65.54 Hz</th>
<th>NRSS = 0.8143</th>
</tr>
</thead>
<tbody>
<tr>
<td>ED</td>
<td>0.2293</td>
<td>0.0629</td>
<td>0.0514</td>
<td></td>
<td></td>
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<tr>
<td>CE</td>
<td>0.1379</td>
<td>0.0514</td>
<td>0.1164</td>
<td></td>
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</tr>
</tbody>
</table>

**Table 1. AR Model Parameters versus Robot Speeds**

$$\Psi_1 = (-0.0835, -0.1614, -0.0905, 0.1670, 0.0875, -0.1100, 0.0505, 0.0898, 0.0575, 0.0877)$$

$$\Psi_2 = (-0.1431, -0.1725, 0.1963, 0.1455, 0.0267, 0.0217, 0.0236, 0.0203, 0.0623, 0.0583)$$

$$\Psi_3 = (-0.1662, -0.1312, 0.2169, 0.0401, 0.0833, 0.1297, -0.0470, 0.0774, 0.1340, 0.0771)$$

$$\sigma_n = (0.0113, 0.0098, 0.0079)$$

**Table 2. Multi-Attribute Assessment**

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>ED</td>
<td>0.2</td>
<td>0.2</td>
<td>0.8</td>
</tr>
<tr>
<td>CE</td>
<td>0.2</td>
<td>0.8</td>
<td>0.2</td>
</tr>
<tr>
<td>F3</td>
<td>0.2</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>NRSS</td>
<td>0.2</td>
<td>0.3</td>
<td>0.7</td>
</tr>
<tr>
<td>Total</td>
<td>0.8</td>
<td>1.8</td>
<td>2.2</td>
</tr>
</tbody>
</table>

**Fig. 1a. Time History (Speed S1)**

**Fig. 1b. Time History (Speed S2)**

**Fig. 1c. Time History (Speed S3)**
Fig. 2a. Frequency Spectrum (Speed S1)

Fig. 2b. Frequency Spectrum (Speed S2)

Fig. 2c. Frequency Spectrum (Speed S3)

Figure 3a. Euclidean Distance

Figure 3b. Cross Entropy

Figure 3c. Normalized Sum of Residual Squares

Figure 3d. Characteristic Frequency