Predictive Maintenance Of Industrial Robots

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Abstract

The objective of this project is predictive maintenance of industrial robots and the possibility of building a condition monitoring system based on the data analysis of robot’s power measurements and detecting the robot accuracy error based on electricity data analysis for predictive maintenance.An experimental procedure is carried out to oversee the correlation between the robot accuracy error and a set of extracted features from current time-series, and to evaluate the proposed predictive modeling.

Introduction

Predictive modeling approach is proposed to detect robot manipulator accuracy errors based on the robot's current data analysis for predictive maintenance purposes.The method considers changes in the distribution of data samples that have been obtained from several executions of one or multiple tasks, using the Kullback-Leibler divergence.Maintenance actions must take place during the acquisition of the training data in order to make possible observing the degradation patterns when adopting anomaly detection approaches.Classical data driven approaches cannot be adopted in the case where no failure data are available in the historic data.Condition Monitoring is a decision making strategy that allows real-time diagnosis of occurring failures and prognosis of future asset and machines/equipment health by continuous observation of the system and its components’ condition.Robots manipulators are key production machines and adopting successful strategies for faults detection and isolation in these tools is widely desired since it might prevent big loss of productivity.

Robot Accuracy and Error Detection

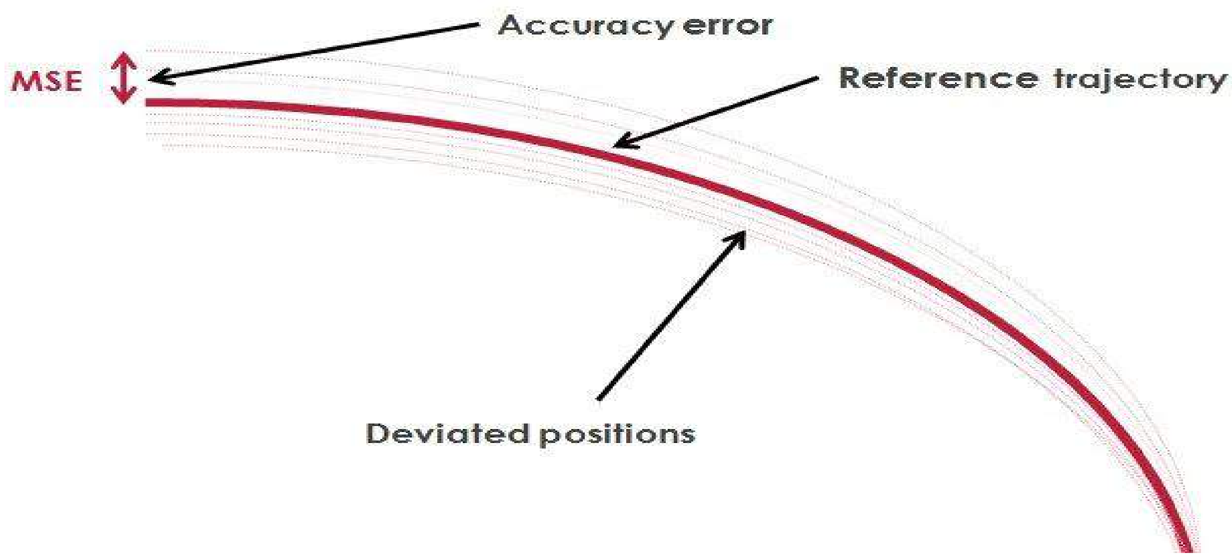
The precision performance of the manipulator is described by two main values specified in the international standard ISO 9283 which defines the performance criteria of robot manipulators. These two values are the pose accuracy and pose repeatability.Besides the assembly or mechanical issues, errors in pose accuracy are generally affected by geometric and non-geometric parameters and mainly caused by defects in the kinematic model.

Robot Calibration Process aims at establishing manipulators parameters' values that affect the accuracy and improving it by performing modifications in the positioning software.This process consists of modeling, measurement, parameter identification and finally implementation of compensation. As a part of the calibration process, an accurate external measuring of the end-effector Cartesian pose of each set of the joint values is performed in various positions.smart-data approach is proposed in this context for condition monitoring and signal-based fault detection of manipulators to oversee the accuracy degradation through power time-series analysis and without using external position and accuracy measurement methods.

The proposed approach for accuracy degradation detection is established by finding a correlation between the electrical signal measured from the robot and its accuracy values[1]. Normally, the correlation that might exist between the fault (accuracy errors) and the used signal (the measured electrical signal) is determined based on a prior knowledge of the system and the accuracy performances of manipulators.

The accuracy value is given by the mean square error (MSE) between programmed positions and measured positions[2] :

$MSE = 1 /n \ Xn \ i=1 \ (\hat{Y} \ i - Yi) \ \hat{}2$



Data Acquisition and Preprocessing

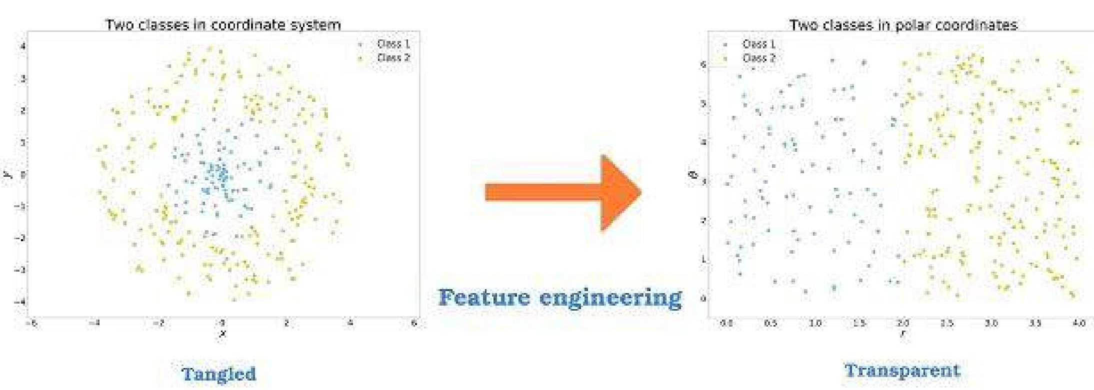
In order to verify this hypothesis, a model is build to predict accuracy errors by analyzing the electricity time-series data. To achieve this goal, we propose to build a regression model between features extracted from electricity time-series data and externally measured accuracy errors of the robot..The general flow of the proposed methodology is exposed in the block diagram.The raw data used in this approach consist of the electrical power measured from the robot and a set of positions of its end-effector while performing a repetitive action during defined periods of time.

The raw data is the spatial positions of the robot’s end effector being measured using an external position tracking device. For a given repetitive motion of the robot, a set of positions of the end-effector can be gathered in a first stage to mathematically model the trajectory of the programmed movement. Based on this model considered as a reference model, the trend of the accuracy errors can be measured by calculating the residuals between new positions and the model defined

Data cleaning operations are performed to remove the non-relevant records captured right before the robot starts moving or right after it stops and only keep the needed values when the robot is performing the repetitive motion[4]. Once the data is cleaned, the power and positions data sets must be segmented into multiple sub-sets where each of them corresponds to some similar patterns related to the repetitive movement of the robot. From each of these patterns of the electricity signal data, a set of features is extracted.

Feature Engineering

Feature engineering is a process of transforming the given data into a form which is easier to interpret. Here, we are interested in making it more transparent for a machine learning model, but some features can be generated so that the data visualization prepared for people without a data-related background can be more digestible.



In order to only keep the relevant ones following features are used:-

- Mean
- Standard deviation
- Kurtosis, Skewness
- Periodicity
- Energy

• Mean and Standard Deviation:

These two measures are useful and simple statistical features. Mean describes the central tendency of the data while the Standard Deviation estimates the dispersion by showing the relation of the values to the mean of the data sample.

m = 1 N X N i=1 xi

σ = vuut 1 N X N i=1 (xi − m)

• Skewness :

Skewness can be described as the measure of the symmetry of a data set around the mean. It is defined as:

S = E(x − m) 3 σ 3

• Kurtosis :

Kurtosis describes the peakedness and how outlier-prone the distribution of a dataset is. It is defined as:

K = E(x − m) 4 σ 4

• Periodicity :

The periodicity is an important feature which gives insight about the seasonality and emphasizes the cyclic pattern of the time series. Autocorrelation is used to verify the existence of periods and determine their duration. The Autocorrelation is defined for different τ lags as :

ACF(τ) = 1 N X N i=1 x(τ) · x(τ + i)

• Energy :

The periodicity of the signal is also reflected in the frequency domain. Based on Parseval's theorem, the energy can also be defined in the discrete-time domain as follows :

Energy = X N i=1 |x(i)| 2

All these recorded three-dimensional points refer to the positions crossed by the end effector during its movement. Hence, a reference trajectory must be first represented by transforming all these spatial coordinates into a mathematical model

Predictive Model and Correlation Analysis

Multiple linear regression as a data model to predict accuracy values based on the extracted electrical features.

A linear regression model with more than one independent or predictor variable is called a multiple linear regression model[3]. The relationship between two or more features and a response by fitting a linear equation to observed data. The steps to perform multiple linear Regression are almost similar to that of simple linear Regression. The Difference Lies in the Evaluation. For a vector X of observations on predictor variables, and a vector Y of responses, the general form of this model can be expressed as follows:

$Yi = β0 + β1xi1 + β2xi2 + .. + βpxip + i$, $i = 1, .., N$

where Yi is the i th response

xij is the j th predictor variable measured for the i th observation

βk is the k th coefficient

i is the i th noise term which is a random error.

Fitting this data model consists in estimating the values of β. Using the least squares approach in this context, the objective becomes to minimize the following :

$X\ i\ (Yi − β0 − β1xi1 − β2xi2 − .. − βpxip)$

Assumption of Regression Model :

- **Linearity:** The relationship between dependent and independent variables should be linear.
- **Homoscedasticity:** Constant variance of the errors should be maintained.
- **Multivariate normality:** Multiple Regression assumes that the residuals are normally distributed.
- **Lack of Multicollinearity:** It is assumed that there is little or no multicollinearity in the data.

However, before modeling this relationship between predictors and response, it is usually more convenient to perform a correlation analysis in order to verify the existence of a linear relationship between all pairs of used variables. The correlation coefficients, as a measure of the linear dependency between two random variables, are calculated for all the variables of the model. For each variable having N observations, the Pearson correlation coefficient between two variables A and B can be defined in terms of the covariance of A and B as follows :

$\rho(A, B) = cov(A, B) / \sigma A\sigma B$

where σA and σB are the standard deviation of A and B

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Linear regression model:
    y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11
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Estimated Coefficients:

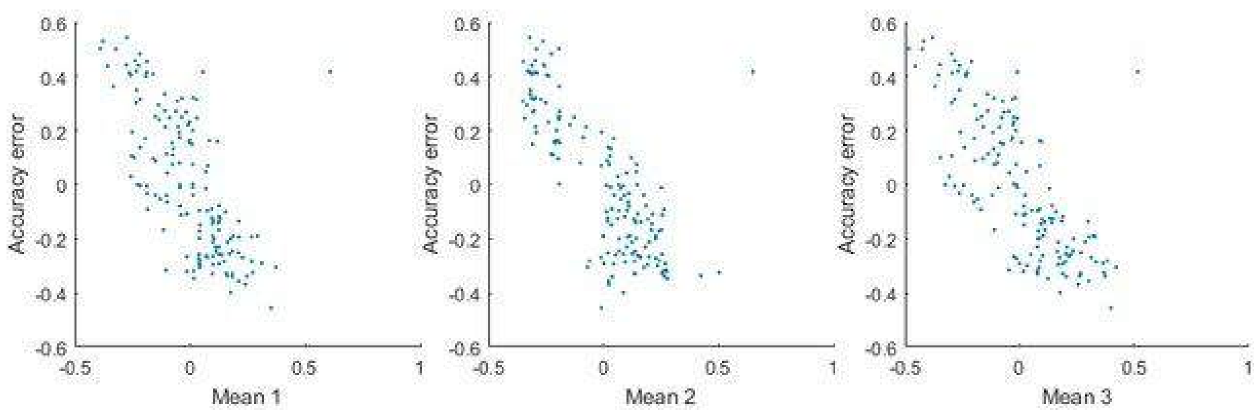
	Estimate	SE	tStat	pValue
(Intercept)	-5.0614e-14	0.0073598	-6.8771e-12	1
x1	1.9161	0.44004	4.3544	2.5278e-05
x2	-4.8473	2.5882	-1.8728	0.063134
x3	4.8122	2.1852	2.2022	0.02925
x4	0.084753	0.093308	0.90832	0.36524
x5	-0.92275	0.50588	-1.8241	0.070232
x6	2.0387	0.59054	3.4523	0.00073128
x7	-2.1557	0.40833	-5.2794	4.7171e-07
x8	4.2066	2.5798	1.6306	0.10517
x9	-5.6189	2.3184	-2.4236	0.016616
x10	-0.05175	0.11375	-0.45495	0.64983
x11	-0.04415	0.067539	-0.65369	0.51436

A correlation matrix is calculated to present the correlation coefficients for each pairwise variable combination. By examining this matrix, where each of its columns represents a separate quantity, the variables with strong linear relationship can be identified

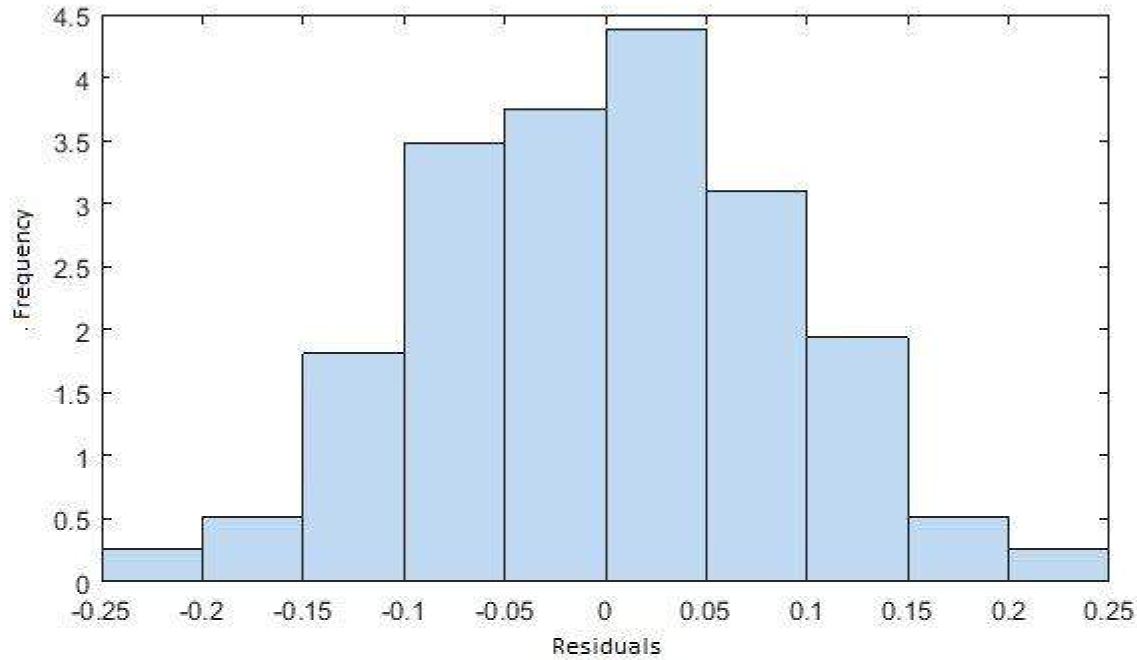
Result

The industrial robot used during this project is Compact and multipurpose robot MZ12, a robot manipulator jointed-arm kinematics for continuous and point-to-point path tasks. It is a six-axis industrial robot powered by AC servomotors, with installed motor capacity of 8.8kW and Repeatability of 0.05 mm . We also used an LTD800 Leica Laser Tracker. It is a coordinate measurement instrument used in many industrial fields, enabling 6DOF tracking for handheld and non-contact 3D-scanning

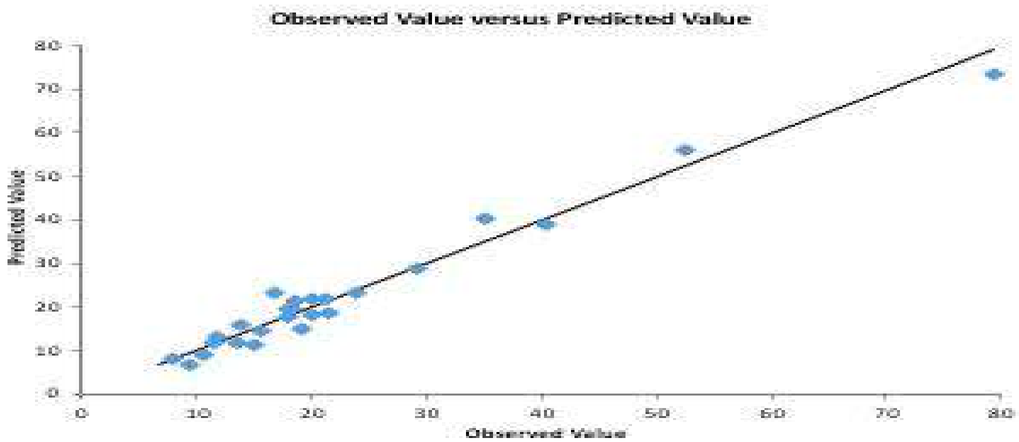
The robot is first programmed to move repetitively between two points A and B for a defined period of time. Simultaneously, the laser tracker records the different positions of the end-effector during its movement with a rate of 100 Hz. s. The reference trajectory is first defined. To build the reference spatial positions data set, the movement of the robot is tracked for a duration of 10 minutes with a capture rate of 800 records per second, leading to data set of more than 20000 records of X, Y and Z axis coordinates values. The reference curve is obtained by applying a linear regression curve fitting on the XZ plane. Based on this model, the accuracy of new tracked positions of the robot end-effector is obtained by calculating the MSE values of these points with regard to the reference model.The recorded power time-series and coordinates data are segmented into multiple profiles with regards to the robot movement.Segment one profile from the power data set as well as from the positions data set. For the training stage, we prepared a data set of current and robot positions data recorded during 18 minutes of the robot movement. After we carried out the feature extraction, we obtained a feature vector of 24columns 8 features from each of the 3-phase currents and 155 rows (observations), corresponding to the different profiles.



Accuracy errors are related to the 3-phase currents. Based on these plots, we can demonstrate that a relatively strong negative correlation exists between the Mean and Accuracy.The skewness extracted from Power L2 and Power L3 have besides shown a relatively strong correlation with accuracy, while skewness extracted from Power L1 has a very weak correlation. We decide therefore to define our final feature vector based on these features while no particular pattern of the data points does exist in the Kurtosis and Accuracy scatterplot, showing that there is a little or no correlation.



Finally fit the data in the multiple linear regression model. The obtained coefficients as well as the specification of the obtained model . As a diagnostic plot to identify outliers, we expose in a residuals histogram plot showing the range of the residuals of the obtained model and their frequencies. This histogram shows that the residuals have almost a normal distribution with no outliers, which highlights the goodness of fit of the obtained model. To better understand the accuracy of our model, we plot the predicted values of accuracy error versus its observed values,This plot shows a strong correlation between the model's prediction and its actual results, which reflects the satisfactory accuracy of the model, despite the small size of the used training data. The obtained RMSE is 0.0916 and thus an MSE of 0.008, which is very close to 0.



Conclusion

Data-driven accuracy error detection approach has been proposed for predictive maintenance of robot manipulators. The specified predictive modeling methodology relies on data analytics of the robot power time-series to predict the accuracy error. The experimental results have demonstrated the existence of a relatively strong correlation between a set of electrical features of the robot 3- phase current and its accuracy values. The obtained predictive model has also shown a satisfactory goodness of fit and high usefulness for predicting accuracy errors based on measured power data. The specified features used within this paper can be employed for further enhanced predictive modeling based on huge datasets of power time-series, to allow an efficient predictive maintenance of industrial robots.

Reference

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