Stress Analysis in Robotic Arm Joint Using PCA-MLP and MLP

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Abstract:

In this paper, two methods are proposed to analyze robotic arm stress overloading. Methods used are PCA (principle component analysis) and MLP (multilayer preceptron). Further, comparison between two methods has been done and an accurate method has been concluded. Mechanical hazards associated with robot manipulator are also discussed with special emphasize on overloading. Methods used firstly find out the stress and then trains the system for risk management due to overstress in future use of robotic arm joint.

Keywords: Robotic Arm, Manipulator, Overloading, PCA, MLP, Stress.

1. INTRODUCTION

The industrial scenario is changing all over the world. Nowadays, in many parts of the world, human workforce has been replaced by robots in developed countries and same change is being seen in developing countries. Robots are identifiable as a unique device with computer aided design (CAD) systems and computer aided manufacturing (CAM) systems, designed to move material, parts tool or specialized devices through variable programmed motions to perform a variety of tasks[1]. As a result of the increased use of robots in human life, the safety of human's have become a hot issue in recent times, as with time many hazards have got associated with robotics. In this paper, overloading or stress on robotic arm has been studied, by implementing two methods, which are PCA-MLP and MLP[2]. Force has been calculated using FSR i.e."Force Sensing Resistor". Further principle component analysis is used with multilayer preceptron, where principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. Other method used is MLP alone.

MLP i.e. Multilayer preceptron is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. In earlier days, neural network approach has been used to find real time motion in robotic manipulator by Xianyi yang and Meng M (1999) which takes in consideration force[3]. Torque sensor based approach for robot arm control using disturbance observer by Hosun Lee, Yonghwan Oh and Jae-Bok Song (2010) has also been used, which refers to torque sensors.

2. PRINCIPLE COMPONENT ANALYSIS (PCA)

Principal component analysis is a variable reduction procedure. It is useful when you have obtained data on a number of variables (possibly a large number of variables), and believe that there is some redundancy in those variables. In this case, redundancy means that some of the variables are correlated with one another, possibly because they are measuring the same construct [4]. Because of this redundancy, you believe that it should be possible to reduce the observed variables into a smaller number of principal components (artificial variables) that will account for most of the variance in the observed variables. Technically, a principal component can be defined as a linear combination of optimally-weighted observed variables.

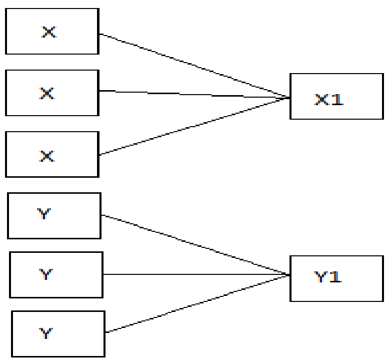


Fig.1 Basic Building Block for PCA

So principal component analysis is a powerful tool for reducing a number of observed variables into a smaller number of artificial variables that account for most of the variance in the data set. It is particularly useful when you need a data reduction procedure that makes no assumptions concerning an underlying causal structure that is responsible for co variation in the data.

3. MULTILAYER PERCEPTRON (MLP)

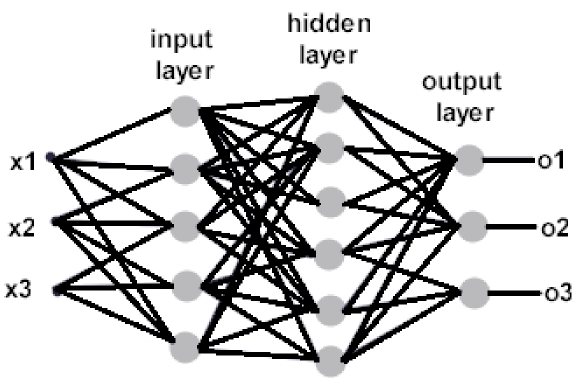


Fig 2: Multilayer Perceptron

The adapted perceptrons are arranged in layers and so the model is termed as multilayer preceptron. This model has three layers: first an input layer and an output layer and a layer in between not connected directly to the input or the output and hence called hidden layer. For the perceptrons in the input layer, we use linear transfer function, and for the pereceptron in the hidden layer and the output layer we use sigmoidal or squashed-S functions[5]. The input layer serves to distribute the values they receive to the next layer and so, does not perform a weighted sum or threshold. Because we have modified a single layer preceptron by changing the non linearity from a step function to a sigmoidal function and added a hidden layer. So now, we have a network that should be able to learn to recognize more complex things.

4. HAZARDS ASSOCIATED WITH ROBOTS

The main hazard associated with the application of industrial robot is the working envelope of the robot[6]. The ability of the robot to move in free space which covers a wide area, change configuration and produce unexpected motion immediately can cause hazards to persons operating or standing in the vicinity of the robot.

Malfunction and human error can lead to the unexpected movement of the industrial robot which include:

a) Aberrant behavior of robots caused by control system faults.
b) Jamming of servo-valves.
c) Robot movement cutting its umbilical cord.
d) Splitting of unions on exposed hydraulic hoses.
e) Fault in data transmission causing a larger than anticipated movement of the robot arm.
f) Faults of welding gun and tooling parts.
g) Programming and other operational errors.
h) Precision deficiency, deterioration.
i) Incompatibility of jigs and other tools.

5. SENSORS

A sensor is a converter that measures a physical quantity and converts it into a signal which can be read by an observer or by an instrument.

5.1 Force-Sensing Resistor

A force-sensing resistor is a material whose resistance changes when a force or pressure is applied. They are also known as "force-sensitive resistor" and are sometimes referred to by the initialism "FSR". Force Sensing Resistors (FSR) are a polymer thick film (PTF) device which exhibits a decrease in resistance with an increase in the force applied to the active surface. Its force sensitivity is optimized for use in human touch control of electronic devices [7]. FSRs are not a load cell or strain gauge, though they have similar properties. FSRs are suitable for precision measurements.

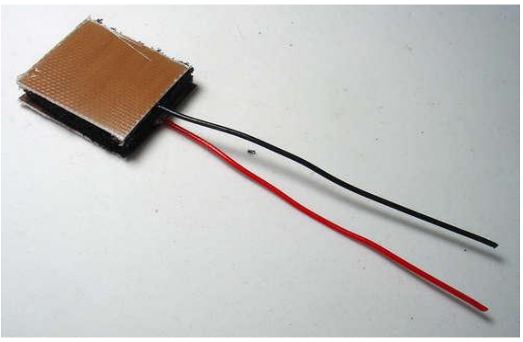
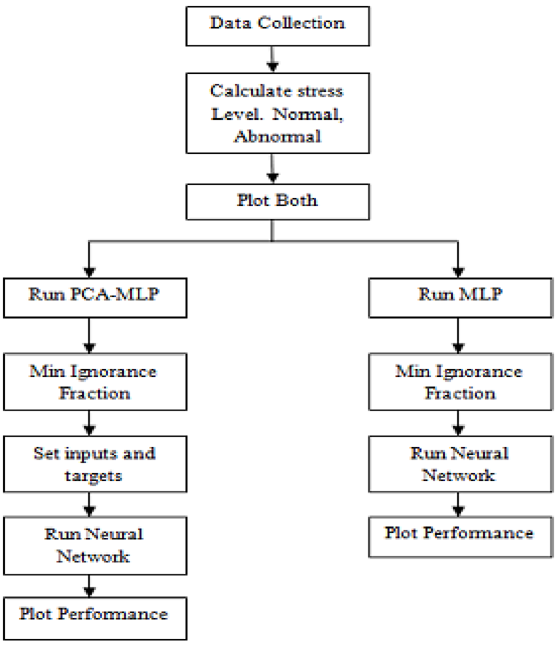


Fig 3: Force Sensing Resistor

6. FLOW CHART FOR BOTH METHODS



7. METHODOLOGY

The methodology followed for MLP and PCA MLP has been briefly described in the following section:

7.1 Data collection from sensors

Data collection was done to have different values of force. FSR i.e. Force sensor resistor is used to collect data from volunteers.

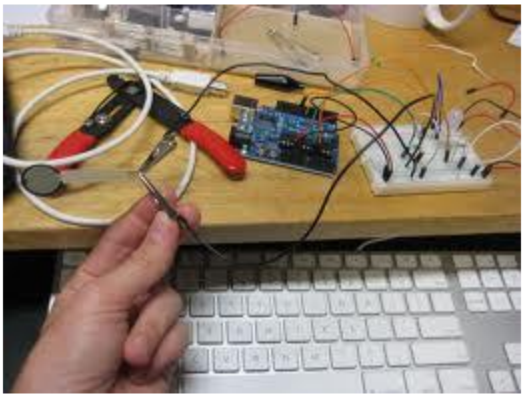


Fig 4: Apparatus

7.2 Calculations

Calculations are done by obtaining stress levels with the help of FSR in between the robotic arm. These calculations are done by applying different pressure to the FSK. Readings taken for stress are on the scale of 0 to 7. Further the normal and abnormal behavior of the stress being applied on the robotic joint is also plotted for MLP and PCA-MLP method. Following are screen shots obtained by applying these methods:

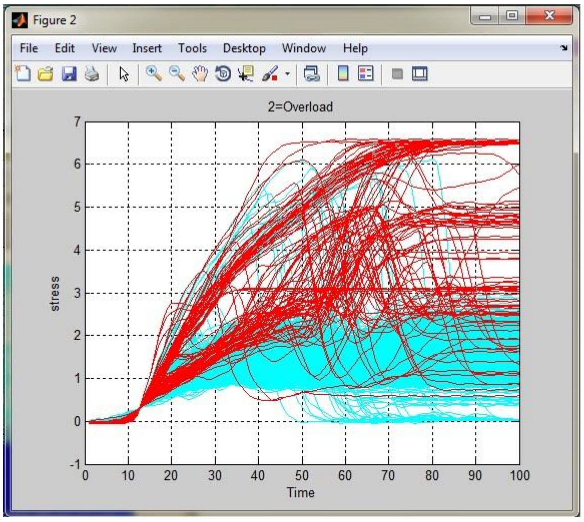


Fig 5: Normal condition with sky blue and overloading with Red shown.

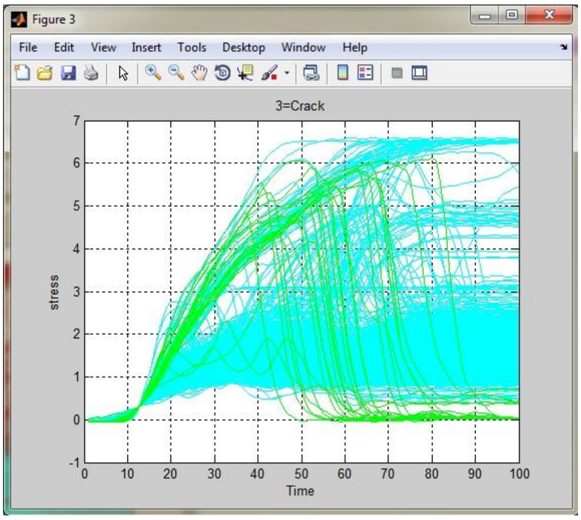


Fig 6: Crack Plot. MLP

Now after MLP methods used to calculate stress in robotic arm joint, next methods used is PCA-MLP .In this also stress is calculated with respect to time and plotted with help of a graph. The screen shots for the obtained results are shown above:

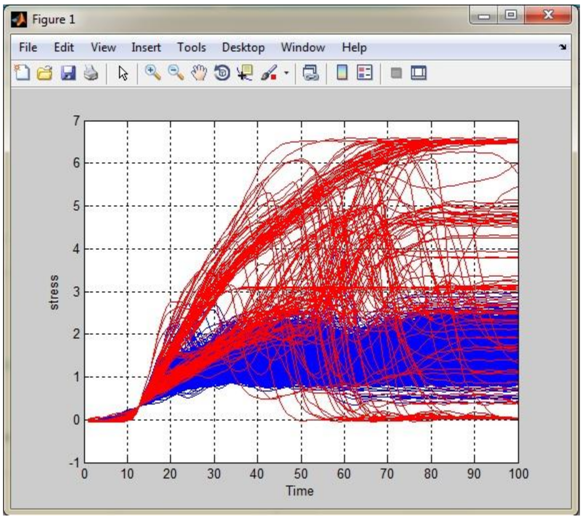


Fig 8: Stress and Time Plot. PCA-MLP

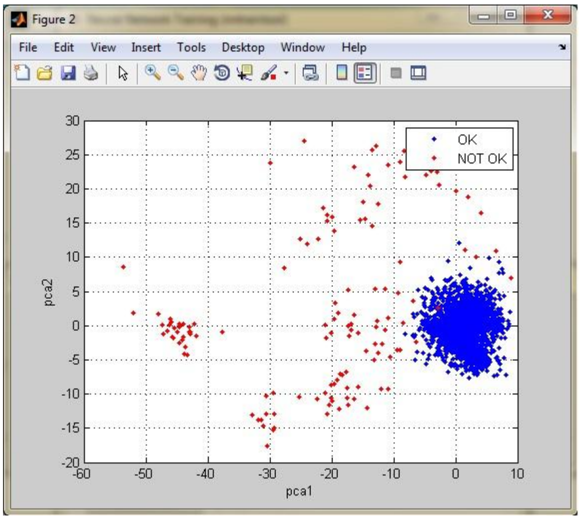


Fig 7: normal and Abnormal condition plotted using PCA-MLP

7.3 Run MLP and PCA-MLP

Both the methods are executed side by side i.e. MLP and PCA-MLP. In MLP after getting the plots for stress in robotic arm, plots are divided into two categories that are overloading and crack. The overloading graph shows the condition in which joint of robotic arm is showing overloading and the other graph shows when the robotic arm joint is going to crack. Further, neural network is applied which is indeed is MLP i.e. Multilayer preceptron. 10-Fold cross validation method is applied to train, validate and test the functioning of the system. Also the system is trained with MLP and results are calculated with accuracy index.

Next method applied is the PCA-MLP. In this MLP method is executed with PCA, which makes it a hybrid method to calculate stress. In this graphs are plotted for stress with respect to time on robotic arm joint. Further PCA is executed which plot a graph that shows normal and abnormal condition of the robotic arm joint due to stress. Also in another graph, the overloading condition and normal condition of working of robotic arm joint is shown. Here PCA i.e. principle component analysis divided different stress conditions in set of two variables, one is normal condition and the other one is abnormal condition. Afterwards, a value of minimum ignorance fraction is given to PCA , which ignore very closely plotted

lines of stress by giving a much more accurate data. Now, MLP is execute after PCA where whole process of MLP is repeated i.e. of training, validating and testing with 10-Flod cross method.

8. FOLD CROSS VALIDATION

A brief introduction to (10) – fold cross validation method is given to illustrate the concept.

In 10 fold cross validation method we use to divide the data into k subsets of (approximately) equal size. Then train the net k times, each time leaving out one of the subsets from training, but using only the omitted subset to compute whatever error criterion interests us. In this data is divided into subsets of three by dividing 100% data into training (70%), validation (15%) and testing (15%).

Training is the process of providing feedback to the algorithm in order to adjust the predictive power of the classifier(s) it produces.

Testing is the process of determining the realistic accuracy of the classifier(s) which were produced by the algorithm. During testing, the classifier(s) are given never-before-seen instances of data to do a final confirmation that the classifier's accuracy is not drastically different from that during training.

Validation is (usually) performed after each training step and it is performed in order to help determine if the classifier is being over fitted[8]. The validation step does not provide any feedback to the algorithm in order to adjust the classifier, but it helps determine if over fitting is occurring and it signals when the training should be terminated.

9. RESULTS

After applying both the methods respectively, different results come into consideration which help in proposing an accurate method. Also a method which is reliable and helps the robotic arm to learn quickly future overloading risks.

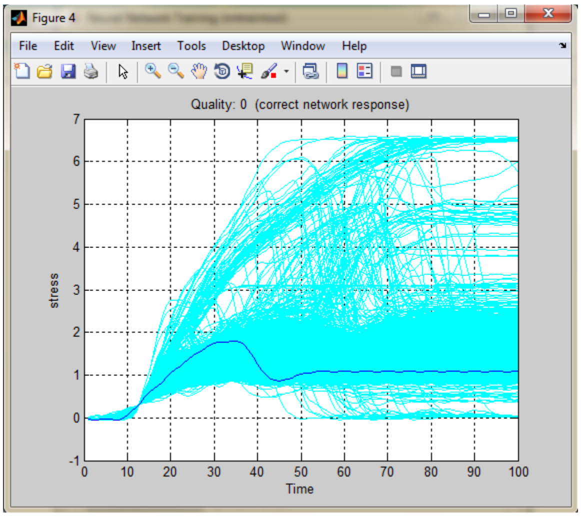


Fig 9: Crack shown due to overloading

Fig 9 shows the value at which crack occurs when robotic arm is working for long time

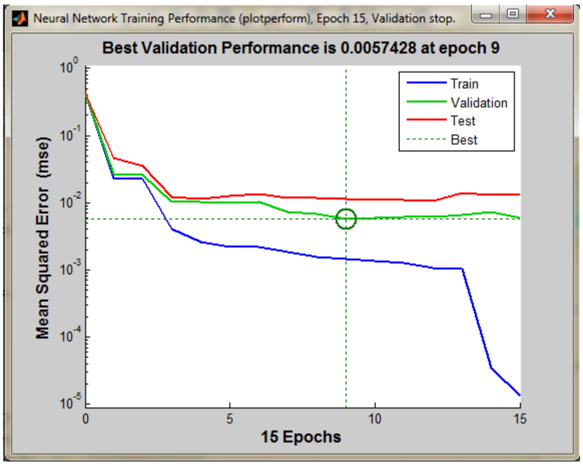


Fig 10: Performance with MLP

Fig 10 shows that with MLP robotic arm manipulator first gets training than validation and goes through training. In MLP the system gets trained after 15 epochs or after 15 iterations and also in this method best validation performance comes at 9th epoch.

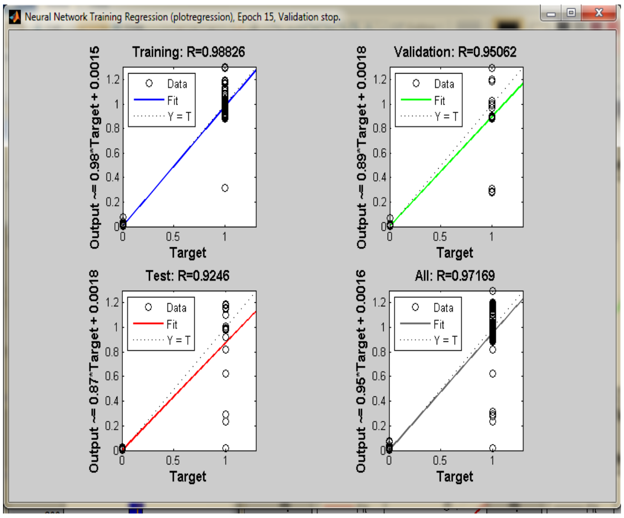


Fig 11: 10-fold cross validation method in MLP

In this graph 10 fold cross validation method is used firstly to train the system, then to validate and in the end testing is done. In this the value of R or regression is 0.97169

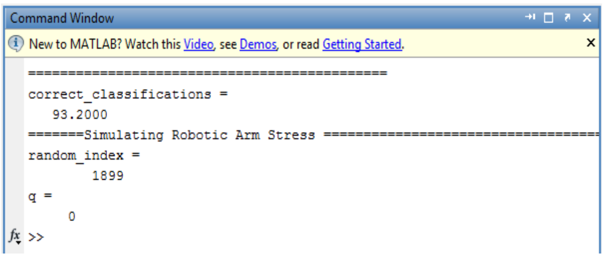


Fig 12: Accuracy of MLP

Fig 12 shows the accuracy of MLP method which comes as 93.20 %. This value of accuracy is more than the previously used MLP methods to find out stress.

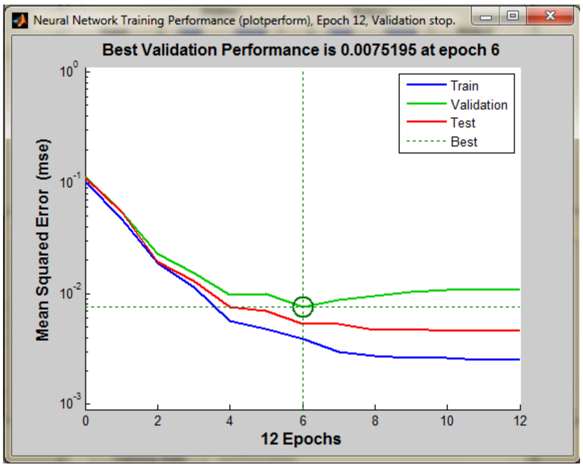


Fig 13: Performance of PCA-MLP

Fig 13 shows the performance graph of PCA-MLP method which shows good improvement than the graph of MLP method. In this the system gets trained in 12 epochs only or 12 iterations only. Also the best validation performance comes at 6th epoch

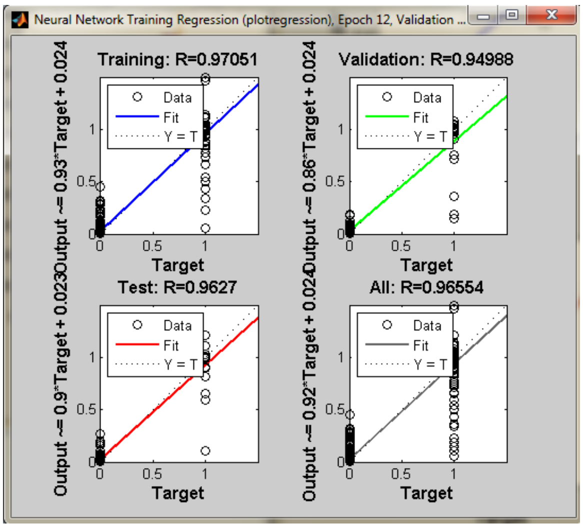


Fig 14: 10 fold cross validation in PCA-MLP

Fig 10 shows the 10 fold cross validation method in PCA-MLP. In this the value of R comes to be 0.96554.

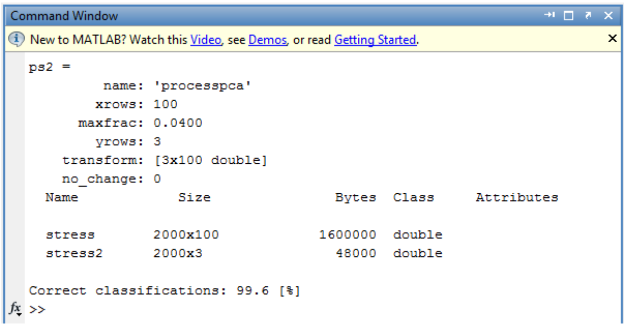


Fig 15: Accuracy of PCA-MLP

Fig 15 shows the accuracy of PCA-MLP method which is 99.60%.

10. CONCLUSION

This journal has proposed two methods to analyze stress on robotic arm joint . These two methods used are MLP and PCA-MLP. In this, firstly the data is collected and then put ot test with two methods. First methods used i.e. MLP trains the system to automatically find out risk of overloading after 15 trainings or epochs and also it is calculated that this method is 93.20% accurate. Whereas the other method that is PCA-MLP trains the system to find out risk in only 12 trainings or epochs, with quick learning also it gives the accuracy of 99.6%. Therefore from the results, it is concluded that PCA-MLP i.e. principle component analysis with multilayer preceptron is more accurate method and also quick method to learn risk management of robotic arm failure due to overstress.

11. FUTURE WORK

Methods proposed can be used in exoskeletons , which is an external skeleton used to help handicap people. As a FSR can be programmed with PCA-MLP method and joined at the joints of robotic skeleton of exoskeleton. These methods can be used with other heavy commercial available weight lifters.

12. REFERENCES

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