Indirect structural change detection based on control algorithm's performance

Ziemowit DWORAKOWSKI\textsuperscript{1}, Krzysztof MENDROK\textsuperscript{1}

\textsuperscript{1} AGH, University of Science and Technology, Al. A. Mickiewicza 30 30-059 Krakow, POLAND

Abstract

There are many approaches to Structural Health Monitoring, most of which require usage of additional sensors for damage detection purposes. There is, however, another possibility: one can detect damage indirectly, based on general performance of the system. Abnormal (novel) data can serve as premise of damage. The problem itself falls into novelty detection category. There are many metrics that can be used in such approach. In case of dynamic systems that require usage of a control algorithm, such metric can be based on control efficiency. In this work such a solution is illustrated on the basis of numerical experiment. Active vibration suppression algorithms are adaptively optimized for particular structure. Then, damage is introduced to the structure. Decrease of performance of the adaptive algorithm can be used to detect damage presence.

Keywords: Structural Health Monitoring, Novelty detection, Systems control, Adaptive algorithms

1. INTRODUCTION

One of the main problems that currently limits exploitation perspectives of various Structural Health Monitoring (SHM) systems is the necessity to have external sensors and data acquisition units which often are difficult and costly to install. On the other hand, a frequent requirement that is often induced on SHM companies by the industry is to work only with the data that is already gathered for current maintenance and operational routines for the system under consideration. For that reason many existing SHM methods of proven performance (e.g. vibrodiagnostics \cite{1}, modal analysis \cite{2}, guided-wave-based monitoring \cite{3-4} and many more) cannot be employed in many particular, industrial scenarios.

Under such circumstances data gathered for operational parameters monitoring can be used to compensate for lack of measurements devoted solely to damage detection and identification. A typical approach require building models for normal or typical behavior of a structure. In its simplest form the approach involve registration of system outputs' ranges and treat values exceeding these ranges as premises of damage, i.e. unusually high temperature measured in the system may suggest overheating of the machinery due to e.g. damaged bearing. A more
advanced approach require measurement of many inputs and outputs of the system and then identify a system model that allows for best transition from inputs to outputs, that is: that allow for a good prediction of output, given the input values.

For the sake of convenience inputs and outputs of the model can be defined arbitrary - where the outputs not necessarily represent a physical output of the system. For example an engine's rotational speed can decrease due to increased load but the system can treat these variables in reversed order, predicting load applied to the system given its rotational speed.

Practically any parameter that is measured due to necessity of machine's control or operational monitoring can be used to build such models. Typically many of them are combined together in novelty detection approaches [5-7]. In this work a novelty detection system is built out of indications of the adaptive control algorithm designed to suppress vibrations of a time-varying system. Since adaptation of a controller is usually performed on a basis of measured quality of regulation, this parameter is usually easily available for further use in damage detection procedures.

The remainder of this paper is organized as follows: section 2 introduces adaptive control and novelty detection approaches with emphasis on algorithms used in this work; section 3 provides experimental evaluation of both the adaptive controller and the novelty detector build on its quality metric; finally, section 4 concludes and summarizes the paper.

2. METHODS’ DESCRIPTION

2.1. Adaptive control

A difference between classic and adaptive control is presented in fig. 1. Although the scheme is simplified, as it does not take into account many existing approaches to adaptive control, it shows the main principle of adaptation, which is to measure current quality of regulation and then propose such changes to regulator parameters which would improve regulation quality in next iteration [8]. Such adaptive controllers are used in cases when either the model changes in time or the environmental inputs change in time with the model being non-linear. In particular, these approaches are often used for vibration suppression [9-13].

![Fig. 1 - Difference between classic and adaptive control. Elements that are usually added to the system to allow it for adaptation are marked in blue](image-url)
In this work the adaptive optimization is performed using a simple $1+1$ evolutionary approach. The regulator is an ordinary proportional-derivative scheme for which four parameters need to be adjusted. The details of the regulator are provided in sec. 3.1. The adaptation algorithm starts with a parent solution (random or pre-optimized), i.e. with a set of regulator parameters. Then, a new candidate solution is created by adding to a previous parameter set a small random vector. The candidate solution is then evaluated and its quality metric compared with its parent. The solution with lower quality metric is preserved as parent and used to generate next candidate solution. The algorithm does not stop - since continuous change of system's parameters is expected, in each iteration system tries to find a solution better than before. In cases when local optimum is already found it results in random movement in parameter space in the neighborhood of the local minimum. If the change is induced in the system rendering current set of parameters to be located outside of the new local minimum, the algorithm starts to gradually move the controller through parameter space towards an area of better values of quality metric.

2.2. Novelty detection

Novelty detection in general relies on building a model for normal data and compare new samples with such a model. The principle of operation of the method is depicted in fig. 2 - regions close to the training samples are treated as normal while those distant from training samples are treated as novel - any data located in the latter is treated as premise of structural or operational change in machine under monitoring. If all the possible operational states are well represented in training data, novel samples usually denote undesired changes in structure: damages, control faults, abnormal operation etc. For a basic insight into various novelty detection approaches reader is referred to one of many reviews on the matter [14-15].

![Fig. 2 - Principle of operation of a novelty detection approach](image)
Since the main aim of this work is to show how control quality can serve as novelty indicator, a simple nearest-neighbor novelty detection approach will be considered: For all the data in a training set the algorithm calculates average distance to nearest neighbor and standard deviation of distribution of this value to serve as a measure of spread of results. For each new element (potential anomaly) nearest neighbor from a training set is found and its distance compared with the mean in the training set. Number of standard deviations that separates new sample and training mean is treated as a novelty indicator with a threshold set on $10\sigma$.

3. NUMERICAL VERIFICATION

3.1 Numerical experiment setup

In order to keep the proof of concept straightforward, a simplified model of active, adaptive vibration suppression was designed. The model include three masses (See fig. 3). The first one is excited with external noise, the second one is required to be damped while the third one serves as input for vibration compensation system. The system changes over time (the masses values are variable).

![Scheme of a model under investigation.](image)

Position and velocity of mass 2 is required to be as low as possible.

A controller is given by the equation (1) - control signal is a weighted sum of four signals: Position of mass 2, velocity of mass 2, position of mass 3 and velocity of mass 3.

$$F_c = -W_1 \cdot x_2 - W_2 \cdot \dot{x}_2 - W_3 \cdot x_3 - W_4 \cdot \dot{x}_3$$ (1)

The weights are subjected to adaptation algorithm as parameters for optimization. A particular set of parameters can be evaluated by running a simulation and estimating a quality metric. For the purpose of this research the metric is given by the equation (2). Although the component associated with vibration of mass 3 does not directly contribute to the initial aim, it was added to reward solutions that obtain suppression of mass 2 vibration without adding excessive energy to the whole system. The final component was added to prevent the algorithm from picking very high weight values which might render the solution unpractical (necessity to excite signal with control force much larger than source of disturbance).

$$Q = 0.9 \cdot RMS(x_2(t)) + 0.1 \cdot RMS(x_3(t)) + 0.001 \cdot (|W_1| + |W_2| + |W_3| + |W_4|)$$ (2)

The algorithm described in section 2.1. is designed to adapt to model changes and keep the quality metric as low as possible.
3.2 Vibration suppression

System adaptation to randomly changing masses with corresponding values of each mass and values of optimized parameters is depicted in fig. 4 along with efficiency of un-adaptive system, for which a pre-optimization was performed once, for initial set of masses. Superiority of an adaptive approach over a pre-optimized one is well pronounced.

Fig. 4 - Values of controller parameters (a), variable masses (b) and efficiency of control for an adaptive and pre-optimized controller (c)
Output of the system without optimization of parameters and after adaptation period is pictured in fig. 5. Although change between result of lack of control (Fig. 5a) and result of control with un-optimized controller (Fig. 5b) is better pronounced than change between outputs of un-optimized and optimized control (Fig. 5c), both are still clearly visible in graphs. It is worth noting that vibration of mass m1 is not included in quality metric and thus is not altered significantly.

**Fig. 5 - Reaction of a system to impulse excitation without control (a), with un-optimized controller (b) and with optimized controller (c)**

### 3.3. Abnormal structural change detection

The anomaly detection algorithm was trained based on 100 000 cycles of control - to learn the typical range of changes of adaptation parameters and its relation to other measured parameters. The inputs to the system were similar as inputs to adaptation algorithm, that is: $RMS(x_2(t))$, $RMS(x_3(t))$ and $(|\mathcal{W}_1| + |\mathcal{W}_2| + |\mathcal{W}_3| + |\mathcal{W}_4|)$. 
After training time a reaction to various system changes was evaluated. The damage was simulated as drop of stiffness in any of the four springs depicted in fig. 3. In each of the cases the change is measured as a percent of change of the respective values. A typical output of the adaptation result along with its respective novelty index is provided in fig. 6. It is worth noting that the adaptation quality metric for intact system (fig. 6a) does not appear to be different than that observed during occurrence of damage (fig. 6b). Despite this fact the novelty detector provides clear indication of a rising anomaly in the system.

![Image](78x443 to 282x613)

**Fig. 6** - Novelty index calculated for three adaptation quality measures. Detection threshold for novelty index set at mean value +10σ.

The spread of novelty indices for all damage cases investigated is provided in fig. 7. It can clearly be seen that the novelty index rises for all of the damage cases investigated. The influence of k1 spring stiffness change is the easiest for detection as it significantly alters amount of energy transferred to mass 2. Damage in springs k2 and k3 has relatively similar effect on novelty index change. Loss of stiffness in spring k4 provides relatively smaller low change to novelty index, still, it is clearly detectable once it reaches 40% of stiffness lost.

### 4. SUMMARY AND CONCLUSIONS

In the article a novelty detection algorithm aimed at detection of damage in dynamical structures was based on adaptive control quality metric. It was shown that three-dimensional quality metric allows for reliable detection of anomalies in all of the system's parts. The method was tested during continuous adaptation to changing system model - the changes allowed for the model (modification of mass) did not trigger the novelty detection algorithm. The general principle of presented research is expected to be easily extendable for more advanced structures, different adaptation algorithms and other types of quality metrics, which is planned in scope of future work.
Fig. 7 - Detection of anomalies for intact state (a) and for four different cases of structural damage (b-e). Vertical lines represent distance from minimum to maximum indication for a given state. Rectangles represent a middle 50% of indications (range from first to third quantile). Threshold for anomaly detection is marked with a red line.
ACKNOWLEDGEMENT

The work presented in this paper was supported by the National Science Centre in Poland under the research project no. 2016/21/D/ST8/01678.

REFERENCES


