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Diagnostics of the ratchet mechanism using the acoustic analysis

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***Abstract* – The paper presents the measurement system for the diagnostics of the ratchet mechanisms based on the acoustic signal analysis. Such mechanisms are common in such devices, as drive elements in bicycles, safe locks or socket wrenches. Their exploitation may lead to wearing out teeth in gears, which is significant in the sport bicycles. To ensure safety of their user, the mechanism's state has to be evaluated. Based on the symptoms extracted from the audio recordings the Artificial Intelligence-based classifier can be used to detect and locate faults related with the pawl degradation. Experiments were performed to verify the system's efficiency during the analysis of the selected gears in the sport (BMX-type) bicycle. They included determining the ability to operate in the noisy conditions and identifying faults by the decision tree, both in the standalone and boosted version. The system's accuracy above 90% proves its applicability to analyze the real-world objects.**

***Keywords* – acoustic analysis, diagnostics of mechanical systems, artificial intelligence.**

I. INTRODUCTION

Mechanical systems are challenging objects for the diagnostics. Their wide implementation requires extensive knowledge about work regime and possible faults that may occur in the structure. Also, because the mechanical components wear out during their operation, it is important to know their actual state to prevent serious damages or learn what has to be done to fix the device. Significant amount of money is devoted especially to diagnose complex, expensive systems, which reliability drives human's safety, such as in aircraft [1] or automotive [2] industry. The key problem here is the lack of knowledge about possible configurations of systems' parameters (despite extensive tests in laboratory or through computer simulations). On the other hand, laboratory experiments with actual devices are time consuming and require sophisticated measurement modules, operating in the Real-Time mode. In cases of large industrial processes (such as in the power plants) the mathematical model of the analyzed phenomenon is the only source of information about the possible problems. It is important to discover, which parts of the diagnosed object are the most prone to faults, which leads to specific guidance regarding the manufacturing and implementation stages (such as recommendations about the periodical testing). The diagnostic procedures should be simple and, if possible, non-intrusive, which poses a significant problem of discovering the actual System Under Test (SUT) state based on the observed output signals.

One of popular elements used in the more complex constructions are ratchet mechanisms. They are the driving force in various devices, such as lifts of lawnmowers, transmitting the external force (often provided by human muscles) to the moving elements, such as wheels. During the operation, such systems often wear out and their efficiency degrades. Therefore it is important to determine their current status, which allows for predicting their lifespan and the timestamp of the incoming damage. As Artificial Intelligence (AI)-based approaches are currently the standard diagnostic approach, they can be used for the task. The important aspect is the collection of measurement data, used to train the fault detection module.

The aim of the paper is to present the diagnostic system for the analysis of the ratchet mechanisms used in the modern bicycles. The decision about the state of the SUT is made based on the acoustic analysis of the sounds generated by the mechanism, from which various features can be extracted. Such scheme is often used in the diagnostics of mechanical systems, where the acoustic signals analysis is employed [3-5]. In other cases these are however objects that can move independently. As this is not the case for ratchet mechanisms, the additional propulsion module must be designed in the measurement system. Features are exploited by the AI-based classifier to detect and identify faults. The main challenges of the presented work included creation of the system allowing for the uniform collection of sound from the bicycle and deciding which sound features should be considered for the decision making.

The paper structure is as follows. In Section II the ratchet mechanisms are presented, especially their construction and work regime. Here possible faults are also iterated. Section III introduces the measurement system constructed to record sound made by the mechanism during operation. In Section IV data extracted to form feature vectors for the AI-based classifier are presented. Section V covers the decision-making module. In Section VI experimental results are presented. The paper is concluded by the summary with future prospects.

II. DESCRIPTION OF RATCHET MECHANISMS

The ratchet mechanisms are widely used in various mechanical systems, such as clocks, bridges, The mechanism consists of the gear or the toothed ring (Fig. 1). Inside there are non-symmetrical teeth and ratchets (or their assembly). The latter must be constantly pushed towards the teeth surface, for instance using the spring. The mechanism requires at least one ratchet to operate. Though there are versions revolving in both directions (like in socket wrenches), the type examined in this work revolves only forward. Mechanisms vary (depending on applications) in the diameter size (ranging from single mm in handheld watches to 80-90 cm in agricultural machines). They also differ in the number of teeth (from 20-30 up to hundreds).

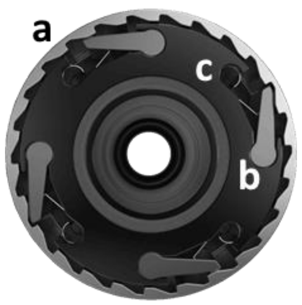

Fig. 1.Illustration of the ratchet mechanism with the visible gear and teeth: (a) ratchet ring, (b) pawl, (c) spring

The most popular application of ratchets is the cyclic industry. They are the part of the bicycle hubs to transmit the propulsion in the forward direction. Their correct operation is crucial for safety of the user. In both professional and amateur vehicles these are elements the most prone to damage, suffering from the physical stress and force imposed by the cyclist. The ratchet mechanism in the bicycle is used to push the propulsion from the rear wheel, while the front one is used to steer the vehicle. The construction allows for the free wheel revolution if the user does not push the pedals.

The mechanisms used in the presented research contain the toothed ring located in the hub's body, which allows for the free, one-directional revolution. Going back (in the reverse direction) is made impossible thanks to 36 teeth located every 10 degrees around the gear. Four ratchets (working in two double-ratchet assemblies) are blocked against the teeth with each forward movement. Because of the gear construction, only two ratchets can be lean against the teeth of the ring. Each ratchet (located in the so-called driver) is pushed by its own spring. The driver receives the propulsion from the toothed ring. During the wheel revolution ratchets are sliding against teeth, generating the characteristic sound of "clicks", i.e. short, high-pitched pulses.

The overall number of 36 teeth of the gear and two assemblies of ratchets give in result 72 contact points. This leads to generating 72 "clicks" during the full wheel revolution (each generated during blocking the ratchet against the tooth). The example of the recorded sound for the complete wheel revolution (fault-free system) is in Fig. Fig. 2. Differences in the amplitude and duration of impulses (in the time domain) are related to the state of the ratchets and teeth. Each pulse is generated by one of two ratchet assemblies, working alternately. It means the even pulses are generated by the first set, while the odd ones are generated by the second set. Pulses representing the particular ratchet assembly are not identical, which is related to the limited sampling frequency of the sound sensor.

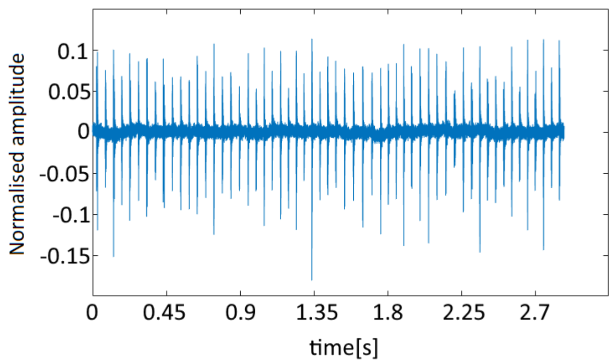

Fig. 2. Results of the ratchet mechanism sound recording

As the ratchet mechanisms are crucial for the proper operation of the bicycle, gaining knowledge about their behavior and possible faults is important for the practical usage of the vehicle. When damaged, the ratchet may cause the bicycle to crash, which is especially dangerous in the professional sports (for example, BMX racing). The possible faults of the mechanism include:

- complete destruction (like breaking) of the ratchet
- partial destruction (like wearing out) of the ratchet
- damage to the spring
- wearing out the tooth in the ring
- breaking the whole ring (which disables the whole construction)
- breaking the teeth inside the ring.

These cases show that possible faults are permanent and belong to either parametric or catastrophic group. The former is more difficult to tackle, as it requires the accurate identification of the current state of ratchet or the tooth. Note that even breaking the ratchet or the tooth does not disable the bicycle immediately. The wheel is still able to pass the propulsion, though the forces delivered by the user are differently distributed.

To properly diagnose the mechanism, it must be disassembled and evaluated by the human expert. This operation is time consuming and requires prior knowledge about its work regime. The procedure can be substituted by the automated system collecting acoustic signals during the mechanism operation and processing them to make decision about the SUT's state. The key problem is to select the measurement conditions, especially domain of the monitored signals and a set of features based on which the AI-based classifier will perform fault detection and identification.

III. DIAGNOSTIC SYSTEM

This section presents the developed system for the diagnosis of the ratchet mechanism state in the bicycle, based on the acoustic signal analysis. It consists of the control and Data Acquisition (DAQ) module and diagnostic subsystem (Fig. 3). The former is deployed in the vicinity of the SUT, responsible for the collection of sound signal, from which features can be further extracted. The latter module processes the signal to extract features and makes decision about the state of the mechanism. Both parts are the conglomerate of the hardware and software parts. To combine all elements into the single entity, two problems had to be addressed. The first one is the sound acquisition, from which reliable information about the ratchets can be extracted. To properly assess the state and position of ratchets, sound made by them has to be recorded by the sensor. The pulses are generated by ratchets only when the rear wheel is moving forward and the crank mechanism remains motionless. The constant speed of the wheel revolution must be ensured to enable sound acquisition for at least one full period. This requires the steady propulsion mechanism for the gear and the sensor determining the number of revolutions.

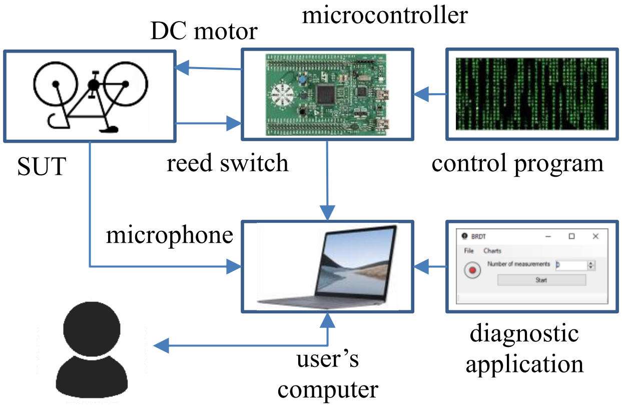

Fig. 3. Measurement system for the ratchet mechanism diagnostics

The second problem is the minimization of the internal and environmental noise, that may influence the feature extraction procedure (as experiments in the isolated conditions, such as anechoic chamber are usually not possible). The former are caused especially by the propulsion mechanism, driving the rotation of the wheel. Therefore the solution should be as silent as possible. The latter are all unwanted sounds generated in the background, which will be recorded by the sound sensor. They should be eliminated at the stage of the system development and during the testing procedure configuration. Below all elements of the system are described in detail.

A. *Structure of the control system*

The control system (Fig. 4) is deployed next to the SUT, connected to it through the propulsion mechanism and sensors. Though it was designed to diagnose specifically ratchet mechanisms in bicycles, its general form remains the same for other devices containing them.

It consists of the following hardware components:

- propulsion module, which contains the DC motor (a), driver roller (b) and transmission belt (c). This module is responsible for moving the gear in the bicycle, which allows for the constant speed of the revolving wheel.
- revolutions counting module, which is responsible for indicating the number of revolutions' periods. It consists of the motionless magnetic field sensor (d), connected to the embedded computer and the magnetic tag (attached to the rotating wheel). Every time the tag closes to the sensor (the wheel turned for another period), the counter is incremented.
- Microcontroller (e), which is the heart of the control system. It runs the software controlling the DC motor through the relay (f) and collects sound samples, passing them to the user's computer .

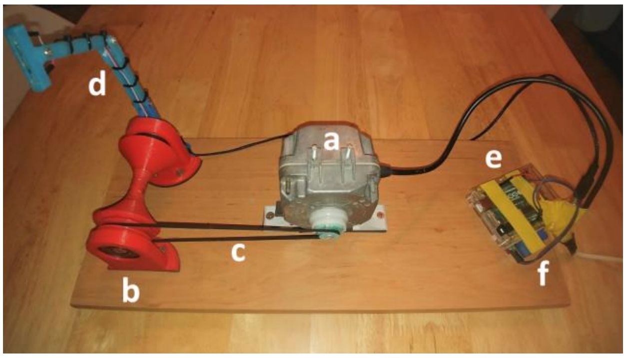

Fig. 4. Picture of the control system

The driving mechanism of the control system is the standard brushless DC motor identical to the ones used in the industrial fans. It is relatively silent, controlled by the microcontroller through the relay. The motor is connected to the transmission belt, which on the other side is based on the propulsion roller that pushes the wheel. The transmission belt was selected because it is quieter than the alternative toothed gear. Also, it is better suited to cooperate with rings that can be produced by the 3D printer. The rings are directly attached to the surface of the of the bicycle wheel's tire. The shape of the driving ring was adjusted to touch the center of the tire. It should also be able to cooperate with various sizes and models of tires.

The module for counting the wheel revolutions uses the reed switch (magnetic field sensor) attached to the regulated arm. The sensor which detects the vicinity of the neodymium magnet, attached to the spoke of the wheel and revolving with it. This way it is possible to programmatically detect the moment of starting the new period. This triggers the process of the sound acquisition, so the observed signals are limited in the time domain to the multiplicity of the revolution duration.

The control task is fulfilled by the Arduino UNO computer, which is in fact the ATMega 328P microcontroller. It is connected to the General Purpose Computer (GPC) through the USB cable. The relay allows for starting and stopping the DC motor. The microcontroller is also responsible for collecting signals from the revolutions counting module. This way it is possible to trigger the diagnostic process from the GPC's application. The control software was created using the Arduino IDE (C-like object oriented language). It runs directly on the computer, without any operating system.

B. GPC and the user application

The second part of the system is the GPC with the diagnostic application. Its purpose is to fetch the measurement process, collect data, extract features and perform the diagnostic procedure. It is connected to the microcontroller, through which it drives the mechanical part of the system. The second element controlled by the GPC is the sound sensor (microphone) attached to the SUT. Its task is to collect sound samples generated by the ratchets, synchronized by the reed switch. Two models were used here: ECM-950 (connected through the jack socket) and Trust GXT 232 Mantis (connected through USB). Both have the passband of 50Hz-16kHz. Acquired samples are processed to extract features and perform fault detection. The additional functionality is the visualization of features, which enables the user to manually observe extracted parameters in the graphical form. The user is able to select the number of revolution periods, for which the samples are collected. The application was created in the .NET technology using the C# language.

C. Data acquisition process

To implement AI into the diagnostic process, feature vectors representing particular ratchet states had to be collected first. The designed measurement system was used during the process of extracting characteristic attributes representing particular ratchet mechanism states for five different bicycles. At the current stage of research, only catastrophic faults have been considered, i.e. destruction of the particular ratchets, with no damage to the teeth assumed. For this purpose the ratchets were removed from the mechanism and the SUT was run to record generated sounds. In all mechanisms ratchets form 2 pairs with constituent elements located at the opposite ends of then toothed ring. The following faults have been considered:

a) fault-free system with all 4 ratchets working correctly.
b) destruction of the selected ratchet in one assembly,
c) destruction of two ratchets – each in the single assembly,
d) destruction of two ratchets from the same assembly,
e) destruction of three ratchets (leaving only one operational).

The experiments were performed in the anechoic chamber to minimize the environmental noise, leaving mainly the GPC and DC motor as its potential sources (Fig. 4). Samples were collected in the "wav" format with the sampling frequency 44.1 kHz and 16 bits resolution.

Fig. 4. Laboratory test stand

IV. DATA ANALYSIS

From the sequence of samples collected by the sound sensor the set of features was extracted. The basis was the time domain, but the additional attributes in the frequency and mixed domain were extracted. The abrupt impulses in the time domain slowly vanish to the reference level, as seen in Fig. 5.

The set of features should be designed to minimize the amount of data representing the specific mechanism's state [6-9]. The original sound files recorded by the microphone contains between 100 and 150 thousand samples for the single when revolution.

The number of pulses p_c during the single wheel revolution should be constant for each period. Combining this information with knowledge about the ratchet mechanism (the number of teeth) gives the first diagnostic symptom, allowing for detecting the fault of the (d) and (e) types (see section III.C). Determining the number or ratchets in the assembly is more difficult and the task is to distinguish the impulse generated by the set of one or two operational ratchets. The first task was then to correctly calculate pulses based on the time-domain analysis.

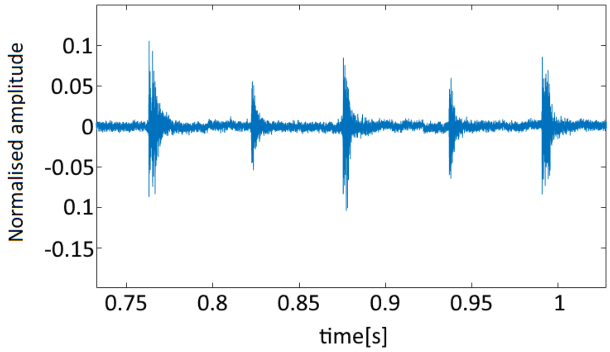

Fig. 5. Time-domain representation of the ratchet-generated pulse

The first step is the pulse detection. The process, described in detail in [10], requires information about noise level. All samples below it are zeroed, leaving the groups treated as pulses. After determining the number and position of each *i-th* pulse it is possible to extract its parameters. These include the pulse amplitude a_i, its duration t_i [s] and energy E_i:

$$E_i = \sum_{j=t_{start}}^{t_{stop}} \left(s_j\right)^2 \tag{1}$$

where t_{start} and t_{stop} are timestamps representing the beginning and end of the pulse and s_j is the sample value.

Additionally the transient analysis of the impulse was decomposed using the Wavelet Transform (WT), which is better suited to describe quickly fading signals than Short Time Fourier Transform (STFT). The configuration of ratchet mechanisms requires analysis of two subsequent pulses should to determine the state of each set. Because sampled pulses generated by the same ratchet differ in shape and calculated parameters, for each set two pulses were decomposed using WT. As the result, the scalogram is obtained, showing the pulse on the frequency-scale plane (Fig. 6). The shape can be described using two parameters: pulse field f_i (the sum of all non-zero components in the scalogram) and its frequency width w_i (difference in the border frequencies of the shape representing the pulse).

The result of the features extraction is the vector containing 21 attributes, describing the specific state of the ratchet mechanism.

$$\boldsymbol{v} = [p_c \quad E_i \quad t_i \quad a_i \quad f_i \quad w_i], \quad i \in \{1, \dots, 4\} \tag{2}$$

Such vectors (supplemented by the fault category *c*) were used to construct the training data set *D* for the classifier. It was filled with data from two mechanisms of the same type. The overall number of vectors contained *D* in the set was 10510.

$$D = \begin{bmatrix} \boldsymbol{v}_1 & c_1 \\ \vdots & \vdots \\ \boldsymbol{v}_n & c_n \end{bmatrix} \tag{3}$$

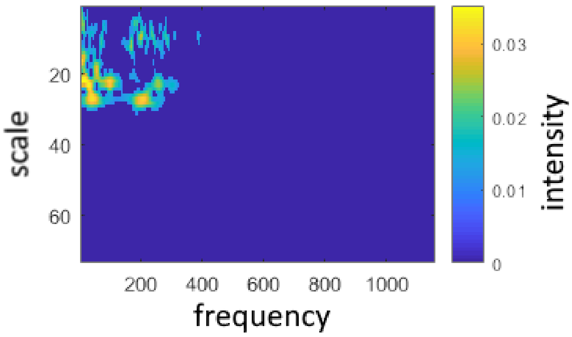

Fig. 6. Ratchet-generated pulse scalogram

V. FAULTS CLASSIFICATION

The efficiency of the prepared measurement system was verified using the Decision Tree (DT) classifier. This is the last part of the diagnostic module, which task is to make the decision about the discrete state of the mechanism (nominal or one of fault categories, pointing at the specific ratchets). The DT is well established in the diagnostic domain [11]. It is memory efficient and represents knowledge legible for the human being. The tree *T* was applied to the system from the Matlab environment (classification learner toolkit). It was trained using the CART method (where during the node generation Gini index is applied) and produces the fault category d_i for the *k-th* feature vector $\boldsymbol{v}$ provided to the input of the tree.

$$d_k = f(\boldsymbol{v}, T), \tag{4}$$

The classifier accuracy (*acc*) is evaluated as the percentage of the correct fault identifications. Five categories were considered (as presented in section III.C, labeled as in Tab. 1. The set construction was aimed at balancing all categories. For these data the decision tree was created with the number of leaves between 5 and 7, which means it is well adjusted to the training data.

Tab. 1. Structure of the data set D

SUT state	Fault code	No. of vectors
Nominal	1	1797
1 ratchet damaged	2	2695
2 ratchets damaged (separate sets)	3	3206
2 ratchets damaged (in a single set)	4	1395
3 ratchets damaged	5	1417

The DT was evaluated five times using the Repeated Random Sub-Sampling Cross Validation. The maximum number of nodes to generate (to avoid overfitting) set to 100. The tree was used as the standalone classifier and after the bootstrap aggregation (i.e. forming multiple trees from different data subsets). In the latter case 50 trees were generated. Average classification results are presented in Tab. 2, where t_{off} is the training time and ton is the time required to classify the single feature vector.

Tab. 2. Fault identification results for the decision tree

DT type	standalone	boosted
$\overline{acc}$ [%]	96.8	98.2
t_{off} [s]	0.69	10.57
t_{on} [us]	1.923	31.25

The ability to distinguish the particular faults is high with the greatest problems with distinguishing between the fault-free SUT and the damage of the single ratchet, as the sound patterns are the most similar (Fig. 7). However, the error rate is about 1% here, which makes the classifier efficient enough for the task.

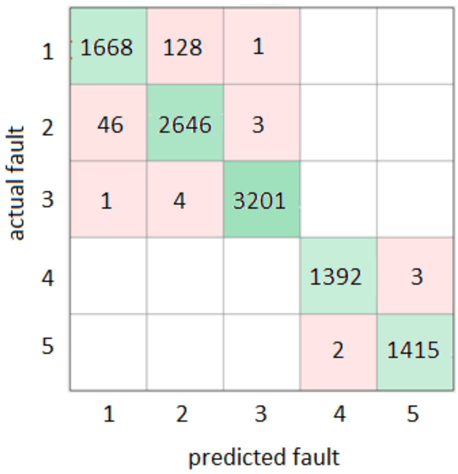

Fig. 7. Confusion matrix for the fault classification.

VI. CONCLUSIONS

The proposed measurement system is able to detect destruction of ratchets in the bicycle propulsion mechanism. The designed control module is able to set the diagnosed object in the configuration allowing for taking repeatable measurements. The decision tree is well suited for the fault location, as the average accuracy is above 95 percent. The future improvements may include incorporation of additional faults (like damages to the teeth) and considering the parametric faults (only partial wearing out of mechanical elements). Also, other AI-based classifiers should be tested on these SUTs. Finally, the influence of environmental conditions (such as additive or multiplicative noise) on the identification accuracy should be tested, verifying the efficiency of the data preprocessing and AI-based classification.

VII. ACKNOWLEDGMENTS

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