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Research Article

Ontology-Based Noise Source Identification and Key Feature Selection: A Case Study on Tractor Cab

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This paper proposes an ontology-based noise source identification method, establishes an ontology knowledge expression model in the field of noise, vibration, and harshness (NVH), and provides an extensible framework for sharing noise diagnosis knowledge in the field. Based on the key features extracted from the noise and vibration signals at different positions and the prior knowledge, mechanical engineers can construct an ontology rule and locate noise sources by identifying the intrinsic relationship between signal characteristics through ontology reasoning. A case study is conducted to demonstrate the effectiveness of the proposed method in resolving the problem of integrating multisource heterogeneous knowledge and exchanging noise diagnosis knowledge information in the field of NVH for agricultural machines. Thus, our study facilitates the sharing and reuse of knowledge and advances the development of intelligent noise diagnosis expert systems to a certain extent.

1. Introduction

With the increased focus on environmental preservation, the reduction of environmental noise has become a popular research topic across various fields. According to the Occupational Safety and Health Act, long-term excessive noise can lead to both physical diseases and psychological disorders. Therefore, it must be actively controlled in working environments [1, 2]. The environment around agricultural machines is harsh. Because of road bumps, engine operation, and vibration of components such as suspension and transmission systems, excitations from different sources are transmitted to the vehicle body panel through the suspension point in the driver's cab and eventually lead to noise emission [3, 4]. In addition, sound waves exert a force on the panel in the driver's cab, causing the cab to vibrate and generate radiated noise [5]. Cab noise is an important performance indicator for agricultural machines, and it depends on the vibration source of the machine, transmission path of vibration, and dynamic characteristics of the cab itself. The internal noise in the cab can be broadly divided into four components: (1) the vibration of the vehicle chassis causes the cab wall to vibrate and generate radiated noise inside the cab; this noise is known as structure-borne noise. (2) Some noise is transmitted into the cab by external noise sources; this noise is known as air-borne noise. (3) Some noise is radiated from noise sources inside the cab. (4) Some noise is generated when the hard surfaces in the cab cause the above three types of noise to bounce back and reverberate; this noise is known as the reverberation noise [6]. Generally, air-borne noise is high-frequency noise and can be reduced by using sound insulation and absorption materials in the vehicle [7, 8]. Structure-borne noise is mainly low- to mid-frequency noise, i.e., lower than 1 kHz, and can be controlled by suppressing structural vibrations [9]. In the past, the design or improvement of a cab system has involved the mitigation of noise signals (which are harmful signals) [10]. The key to more effectively reducing the internal noise in cabs is

to locate the noise signal source and identify the corresponding characteristics.

Two critical steps involved in noise reduction are (1) the analysis and extraction of the characteristics of noise signals in cabs and (2) the establishment of the relationship between the source components and vibrational noise performance of the entire machine [11, 12]. To effectively control the vibrational sound, it is necessary to identify the main vibration noise source and its characteristics in agricultural machines and establish the relationship between the vibrational noise source and the vibration noise of the entire machine. These steps will allow the prediction and control of vibration noise in the design stage. In general, noise source identification approaches can be categorised into those based on simulation and those based on experiments. The former category uses numerical analysis methodologies and is suitable for quick system-level response prediction during the product design phase, whereas the latter category requires data acquisition and is usually employed for dynamic response analysis during the product-testing phase [13]. In some circumstances, methods of both the categories are combined for complementary use. The structure of agricultural machines is very complicated. The simulation-based methods are generally subject to model accuracy problems, thus affecting the reliability of the simulated results. The experiment-based methods can potentially obtain considerably better results, providing well-collected datasets.

However, the postprocessing of experimental data still heavily relies on manual calculation and empirical judgment, which can be inefficient and erroneous because of human error. Furthermore, because of the complexity of the diagnostic object, limitations of the test methods, and inaccurate knowledge [14], different diagnosis methods are usually required to tackle different problems under different circumstances. Therefore, the direct integration and sharing of test data, diagnostic information, and empirical methods can be challenging in most cases. The numerous uncertainty-related problems encountered when performing noise diagnosis significantly affect the capability and efficiency of subsequent vibration and noise reduction experiments.

The basis for noise diagnosis is to establish the correlation between the signature noise signal and the noise source. Ontology, as an expression concept for describing knowledge models at the semantic and knowledge level, can provide a standardized description of the concept [15] and has been widely used for knowledge sharing and reuse across different domains. Ontology is capable of deducing intrinsic or implicit uncertain connections [16]. Therefore, it can provide clearer and more accurate judgments of signal characteristics and noise sources as well as support a common understanding of knowledge in the field of noise, vibration, and harshness (NVH). Thus, ontology can be used as a powerful tool to sort, summarise, and refine prior procedural knowledge of NVH diagnosis to overcome the difficulty of information sharing and reuse in this field [17].

The focus of this study is to establish a feasible method that can provide an extensible framework for sharing information and noise diagnosis knowledge in the field of NVH. We develop an ontology knowledge expression model and identify the potential links between signal characteristics based on the prior knowledge of mechanical engineers. A case study is conducted by collecting sound and vibration signals from the driver's cab of a tractor. Parotic noise signals are collected at the operator's position, and vibration signals are collected from different parts of the vehicle. The characteristics of the noise sound signal and sound vibration signal are matched using the ontology knowledge expression system. If the match is successful, the noise signal is considered to be related to a specific vibrating part. The exact features by which such a correlation is represented can also be deduced at the same time. The study results are expected to facilitate the construction of an ontology rule, realise highly efficient and intelligent noise source localisation through ontology reasoning, and assist engineers in subsequent experimental research and analysis.

2. Related Works

Ontology has been widely used across different domains to realise knowledge sharing (i.e., to obtain, describe, and represent relevant knowledge). It is a framework with customised knowledge, and its core function is to define a special dictionary for one or multiple domains, thus achieving consensus across various ontologies in terms of cross-communication [18]. It can replace the human brain in diagnosing and locating noise signals by providing more rapid reasoning and higher analysis efficiency. Moreover, its intrinsic expansibility facilitates the addition of new data, content, and conditions.

To create an ontology that can be interpreted unambiguously and used by software agents, we require a syntax and formal semantics for OWL. OWL is a semantic web language designed to represent rich and complex knowledge about things, groups of things, and relations between things. OWL is a computational logic-based language such that knowledge expressed in OWL can be exploited by computer programs, e.g., to verify the consistency of that knowledge or to make implicit knowledge explicit. OWL supports greater machine interpretability of content than XML, RDF, and RDF Schema by providing additional vocabulary along with formal semantics [19]. Ontology, which is a term borrowed from philosophy, refers to the science of describing different kinds of entities in the world and how they are related. An OWL ontology may include the descriptions of *classes*, *properties*, and their *instances*. Given such an ontology, the OWL formal semantics specifies how to derive its logical consequences, i.e., facts not literally present in the ontology but entailed by the semantics [20]. Ontology has a very strong expressive inference functionality, thus ensuring the correctness of knowledge description. It is an important information description methodology widely used in the computer science domain [18, 21].

Ontology is also a model-building process used to assemble knowledge related to a particular domain, aiming to effectively organise, represent, share, and emphasise important information. Ontology itself is not used for problem-solving but for providing resources and reference materials to any problem of interest. Therefore, the method of applying an ontology framework to practical user cases is the key.

The ontology modelling process involves establishing the intra- and interconcept relationships within a knowledge system. Figure 1 shows this process. The process is described as follows:

(1) Domain analysis: this process involves defining scopes, features, contents, contributing factors, properties, and their relationships with respect to the domain knowledge and subsequently summarising and categorising them based on established principles such as language meaning and domain characteristics.

(2) Key concept extraction: after knowledge categorisation, the key concepts need to be extracted for knowledge representation. An ontology can further be formulated after reorganising these key concepts and is usually treated as the basic knowledge units for applications.

(3) Ontology description: the ontology can be represented using OWL. As in the case of natural languages, the dimensions need to be defined for computer language prototyping. This definition usually refers to the concepts, properties, and methodologies of the object of interest, which are the key features for describing the type of object and the features and applications related to the object. It is a way to define from which perspectives we can effectively describe the knowledge. For each individual ontology, multiple dimensions are usually required. Moreover, for an ontology system, the hierarchies, structures, and organisational relationships between the ontologies need to be included in the description.

(4) Ontology modelling: this involves obtaining an ontology model and applying it to automate the defined user cases.

Several studies have analysed NVH problems in agricultural machines [22], mostly using ontology-based diagnosis methods. Only few studies have tried to solve the problem of noise diagnosis in agricultural cabs by combining ontology and signal characteristics. Therefore, this study introduces ontology for the noise diagnosis of agricultural machines. The noise diagnosis process is intrinsically a process that analyses a noise signal based on existing knowledge, which mainly includes the relationships between the noise and vibration sources. When analysing noise signals using an ontology-based approach, the semantic relationships between the noise sources, between the vibration sources, and between the noise and vibration sources are first established using ontology. Subsequently, the signal features are extracted based on input ontology noise signal data when performing noise diagnosis. The high-frequency features are individually analysed and converted to a collection of data concepts that can be recognised in the ontology by a standardised process. Finally, the noise sources are located using the noise diagnostic rules presented in this study. This method can serve as a basis for improving the accuracy and reusability in noise diagnostics.

In the mechanical noise diagnosis domain, because of the correlated features among the datasets, an advanced logic inference capability is required for knowledge representation. To extend the flexibility of ontology to meet the system design requirements, a tool that can be used to effectively perform numerical calculation is needed. Based on the above considerations, a web-based language called the semantic web rule language (SWRL) is selected for our research.

3. Expression of Ontology Knowledge for Noise Diagnosis in Cab

3.1. System Framework. In this study, Protégé 5.2 is used to build the ontology and rule-based ontology management system. When developing the prototype system, the editing function for ontology and the rules are realised using the SWRL, which provides necessary support for constructing the prototype system. The SWRL is a rule-based semantic web language, which presents rules in a semantic manner and performs reasoning based on the "rule + inference engine" method. The Pellet inference engine is used in the deduction process, which is an important step in correlating the signal data with the noise sources.

The detailed workflow is as follows:

Step 1. A concept knowledge base is determined and generated based on the professional experience of mechanical engineers. The basic concept knowledge related to the field of NVH is based on professional experience, relevant literature, and standard specifications. The required signal features are subsequently extracted and represented.

Step 2. The knowledge is converted into ontology and SWRL rules, and the correlation models are subsequently obtained. Protégé 5.2 and its plugins (e.g., SWRL editor) are used in this step.

Step 3. The ontology management system extracts the implicit knowledge from the knowledge base based on the SWRL rule engine.

Step 4. The noise signal source is located by inputting the collected signal and performing Pellet reasoning.

Figure 2 provides more details about the system.

3.2. Building Domain Ontology. Domain ontology helps describe the interconcept relationships in a specific field. Because the knowledge contains significant domain characteristics, domain ontology can more accurately and effectively represent the knowledge, thus allowing the modelling of design knowledge domain ontology [23]. The "domains" are constructed based on the requirement of the ontology builder. The overall thought process is to identify problems to be resolved; identify domain areas; carry out domain analysis; construct a domain ontology model; and describe classes, properties, and entities. This information is later integrated with the ontology based on the relevant engineering practice to express the knowledge of the problems to be resolved and extract the rules necessary for performing reasoning. Finally, a conclusion is drawn, and

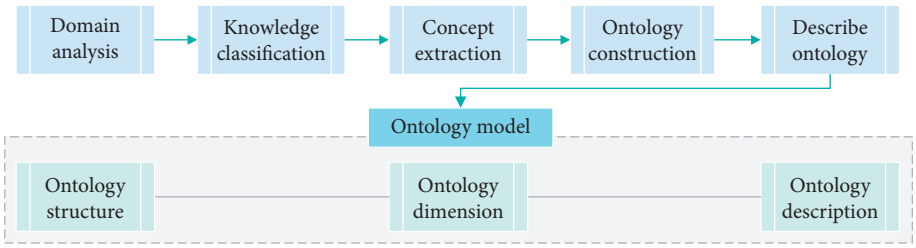

Figure 1: General process of building the ontology model.

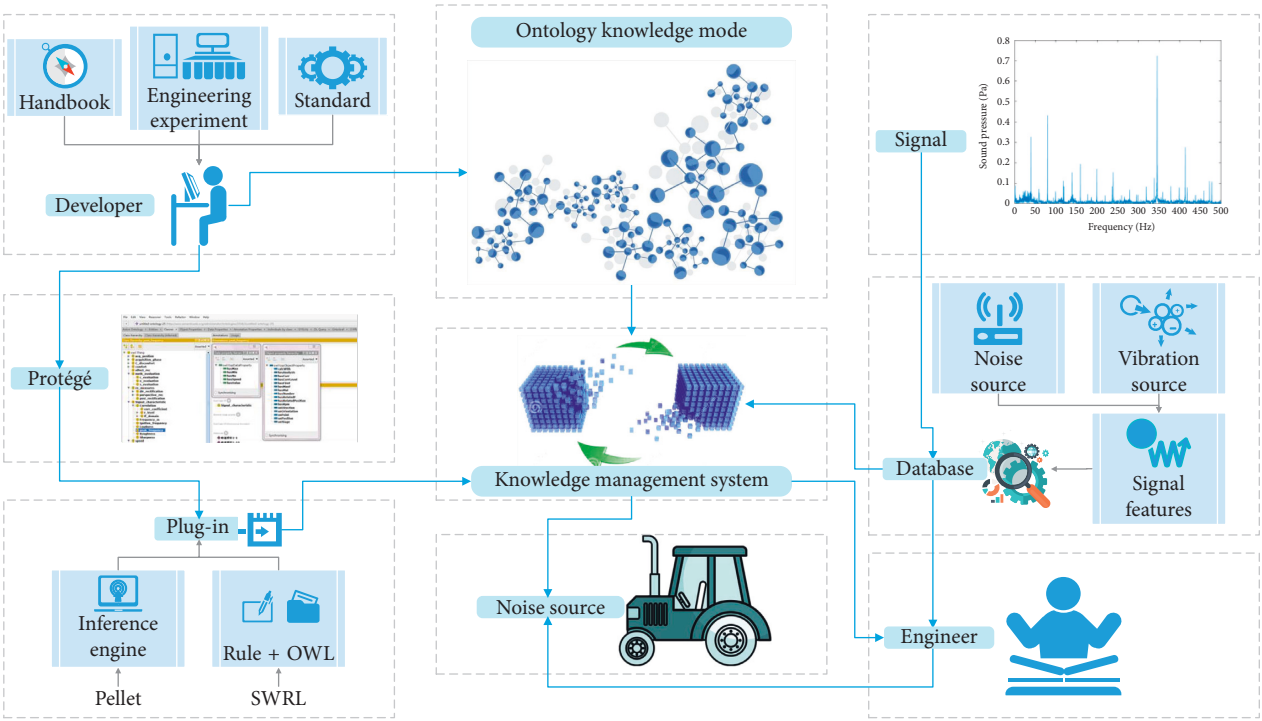

Figure 2: Prototype framework.

the problems are resolved. Figure 3 shows the process of constructing the domain ontology.

Although many open-source software applications are available for editing and generating ontology, the Java-based open-source ontology-editing tool Protégé, developed by Stanford University, is the most widely used software for a comprehensive analysis and evaluation of the functional characteristics of ontology owing to its practicality [24]. In our study, the ontology model is constructed using Protégé, the rules are described using the SWRL, and the reasoning is performed using the Pellet inference engine. The seven-step method developed by the Medical School Department of Stanford University [25] is used in our research to construct the model.

3.2.1. Determining the Domain and Scope of the Ontology. The domain and scope of the ontology are identified through a series of basic questions (BQs) and system capability questions (CQs):

BQ: Which domain of expertise will be covered by the ontology being built?

A: the field of NVH in agricultural machines

BQ: What is the purpose of building this ontology?

A: to realise knowledge sharing and discover hidden rules in the field of NVH; achieve effective organisation and rapid reasoning of the noise diagnosis knowledge in agricultural machines with higher efficiency, less human labour, and lower cost; and provide support to improve acoustic comfort in the cab

BQ: Who is the user of the developed ontology?

A: a mechanical engineer

CQ: What type of elements will be covered in this study?

A: rotation speed, acquisition position, acquisition phase, signal characteristics, comfort, and improvement approaches

CQ: Where did the signal characteristics used in this study come from?

A: the parotic noise signal and vibration signal of the subcomponents of an agricultural machine

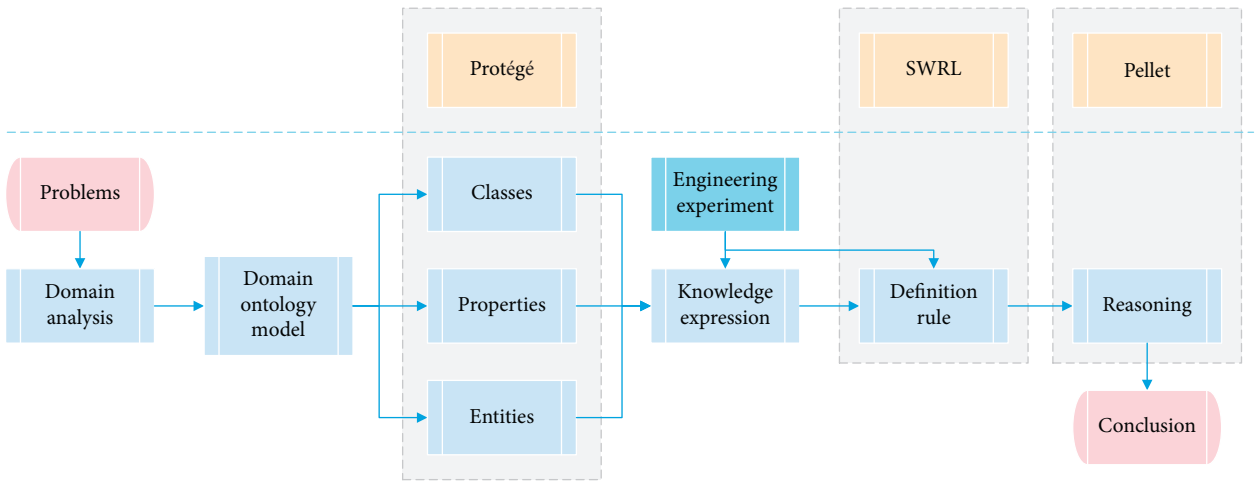

Figure 3: Process of building the domain ontology.

CQ: What types of signal characteristics are covered in this study?

A: peak frequency, ignition frequency, high-order frequency, loudness, sharpness, roughness, and correlation

3.2.2. Considering the Reuse of Existing Ontologies. When constructing a new ontology, reusing existing ontologies is the most effective method if the system needs to interoperate with other application platforms and if this application platform is integrated with a specific ontology. In this study, no existing ontology is reused because very few studies have explored the combination of ontology, vibration comfort, and noise comfort. All the ontologies are constructed independently in this study.

3.2.3. Enumerating the Important Terms in the Ontology. First, a comprehensive list of terms associated with NVH is required. The entire vehicle structure consists of many complicated subcomponents such as the engine, cab, safety frame, and hoarding. Because the objective of ontology is to perform noise source identification and key feature extraction, only the structural framework required and involved in the ontology is considered in the study. The noise source and vibration source signals at different positions are collected at different speeds and preprocessed for extracting and correlating the characteristic signals. Although many different signal characteristics exist, only the commonly used and representative ones are selected in this study, i.e., the peak frequency, ignition frequency, frequency doubling, loudness, sharpness, roughness, and correlation. Depending upon the actual case, the required signal characteristics can be selected or extended from the characteristic library. The correlation level consists of four dimensions: Levels 1, 2, 3, and 4. The contents involved in the experiments are further selected and decomposed. Figure 4(a) provides more details about the developed ontology.

3.2.4. Defining the Classes and Class Hierarchy. The concepts related to the field of NVH are treated as classes. Defining the classes and properties is an important stage in the ontology design and development process, and the two activities must proceed in parallel. The ontology is constructed in a top-down sequence. We first start with one super class that combines all the different elements such as working conditions, collecting locations, subsystems, signal characteristics, causes of discomfort, and improvement approaches. This super class is then decomposed into classes and furthermore into subclasses. The content included in each subclass is considerably more detailed and concrete.

3.2.5. Defining the Properties of Classes. The properties of the concepts are defined simultaneously with the construction of the class hierarchy. When a class is defined, a description of its properties is given. The properties are further divided into the object property, data property, and annotation property. The object property is established based on the relationship between classes. Figure 4(b) shows the properties of the main classes of the developed ontology. Examples are *onPosition* and *hasCorrLevel*. *onPosition* represents the location from where the signals are collected and relates to the noise source or vibration source, whereas *hasCorrLevel* represents the classification of the degree of correlation.

The data property is established based on the relationship between the concept and data. The characteristics of the instances of each class are defined by the data property. Figure 4(c) shows the main data properties of the developed ontology. As a simple example, we consider the signal characteristic classified as the "ignition frequency." This can be represented in the ontology as an instance of the signal characteristic class where the "ignition frequency" is the data property. Further data values can then be added. The following data types mainly describe the types of values that can define the properties: string, number, Boolean, enumeration, and instance type. For example, the "ignition frequency" can have the value type "Float" and can be quantified by using values such as 80 Hz. Furthermore, the function of the annotation property is to clarify the data and explanation by inputting a comment on some elements of the ontology wherever it is needed.

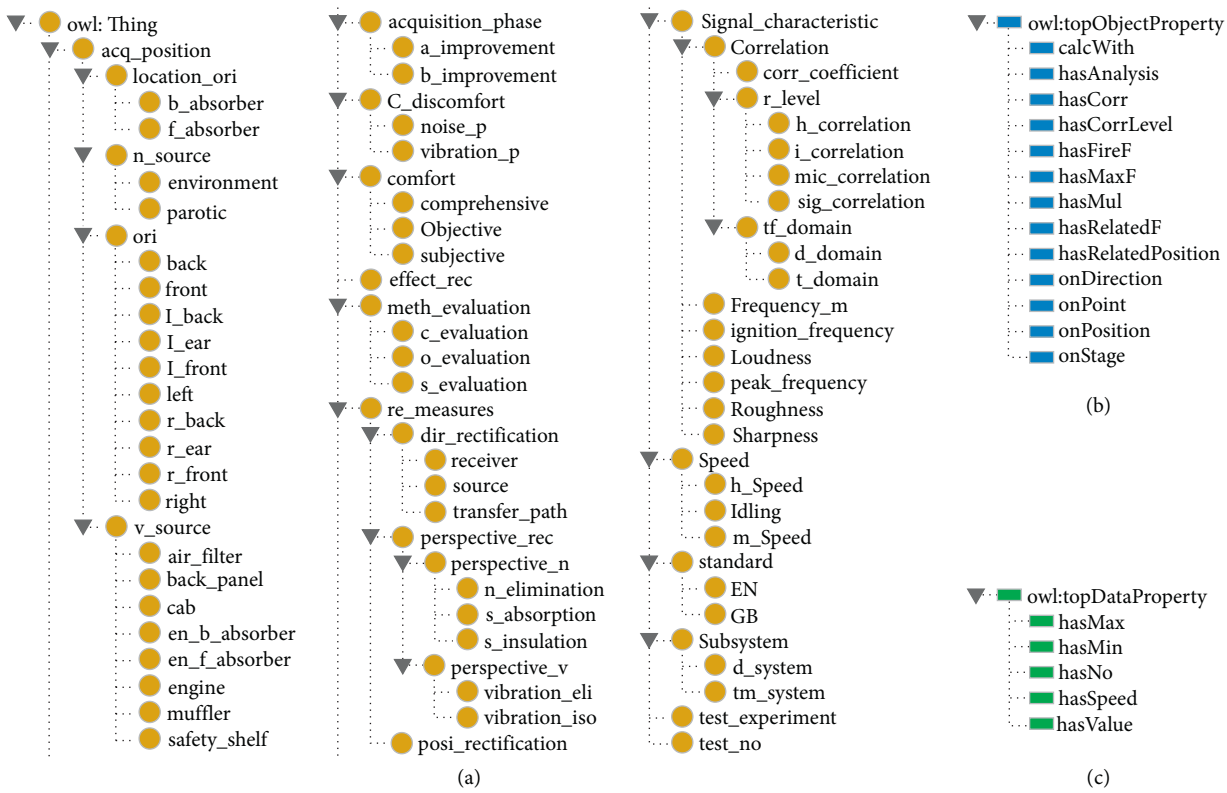

Figure 4: Developed ontology in Protégé-OWL 5.2.

3.2.6. Creating Instances. A case study is conducted based on actual experimental data. The classes, entities, and properties are correlated in Protégé to express the knowledge, as shown in Figure 5.

3.2.7. Defining SWRL Rules. Ontology only provides the structure and relationship between different components. The integrated inference engine included in Protégé can perform deduction if a particular entity belongs to a class but cannot derive the relationship between different classes. To satisfy the correlation requirement, the SWRL rules are employed to improve the flexibility of the ontology. The SWRL is an inference function associated with ontology that provides interoperability between the rules and ontology (semantics and inference). A typical example is the correlation between parotic noise and signal measurement location in an agricultural machine. The SWRL rules are defined as follows:

SWRL: test_experiment(?test)^hasCorr(?test,?corr)^corr_coefficient(?corr)^calcWith(?corr,?position)^onStage(?corr,b_improvement)^hasValue(?corr,?corrvalue)^r_level(?corrlevel)^hasMax(?corrlevel,?maxvalue)^hasMin(?corrlevel,?minvalue)^swrlb:greaterThanOrEqual(?corrvalue,?minvalue)^swrlb:lessThan(?corrvalue,?maxvalue)^hasNo(?test,?no)^hasNo(?corr,?no)->hasCorrLevel(?corr,?corrlevel)

In this case, the SWRL rules comprise atoms connected by the caret symbol "^". There are four types of atoms in this ontology: class atoms, individual property atoms, data property atoms, and object property atoms. The question mark symbol "?" represents the variables in each atom. A named class and a variable can represent the class atom in the ontology; for example, *(?test)* would express the OWL element "*test_experiment*" class in the class atom, while *(?corr)* would be the "*corr_coefficient*" class in the OWL. An individual property atom consists of the OWL ontology of an object property along with two variables, each representing an individual in the ontology. As an example, "*hasCorr*" forms an object property for test_experiment and can be shown in full as *hasCorr(?test,?corr)*. Data property atoms comprise the data property and two variables, of which the first represents an OWL individual and the second is either a value or a data property. Taking the Value of a correlation coefficient as an example, the Value is a data-valued property, which can be represented by *hasValue(?corr,?corrvalue)*.

The function of the rule is as follows: input the correlation coefficient (specific numerical value); if the rule matches (in the range of correlation coefficients), it is inferred that the parotic noise signals are related to a certain position. The feature of this correlation is represented by the correlation.

3.3. Feature Extraction. The noise is analysed based on the correlation between the noise signal and noise source. The key step in the noise diagnosis is to express the complex relationship as knowledge in the system knowledge base. The vibration signal is characterised by many different indicators, each exhibiting a different level of sensitivity to the signal. To select a high-quality characteristic indicator to fully express the relationship between the vibration source

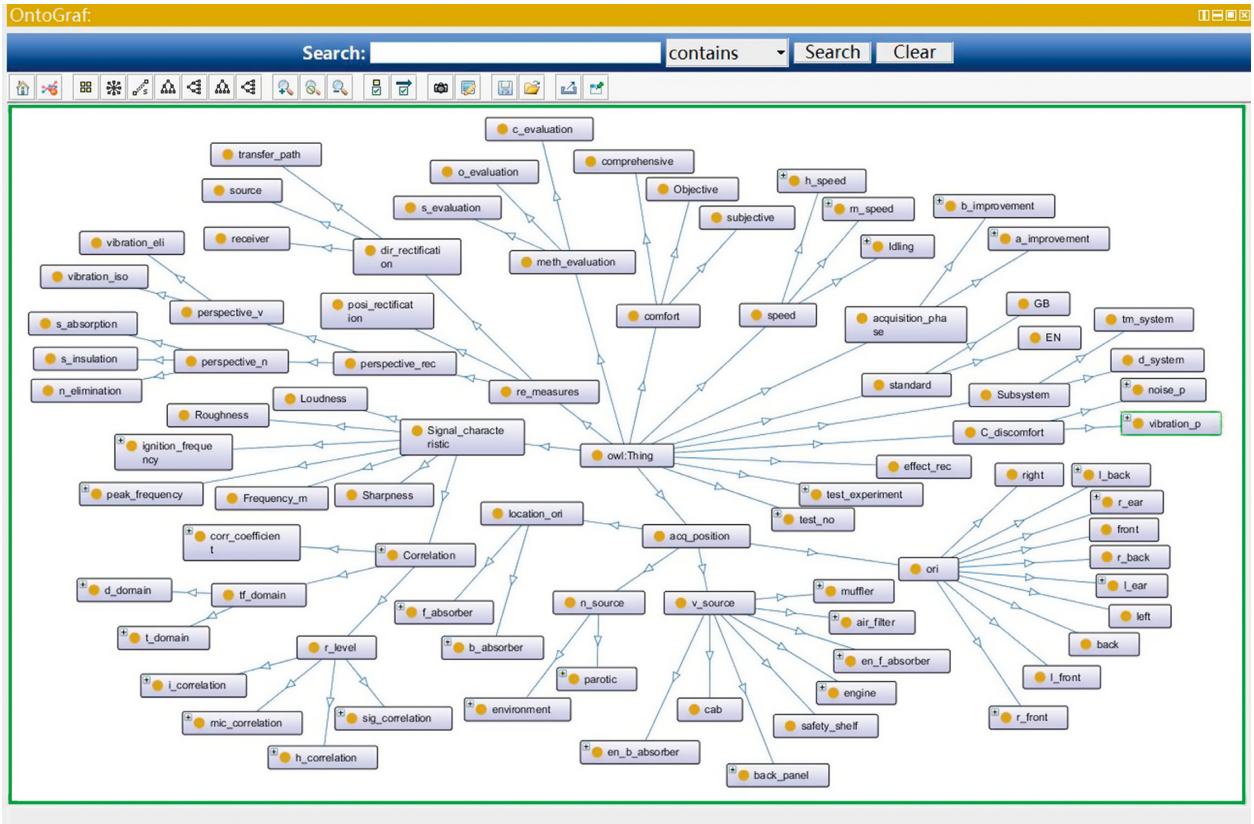

Figure 5: Ontology knowledge expression.

and noise signal, several common signal features with the highest appearance frequency and closest relationship to the features considered in our study are extracted from the noise signal. It should be noted that the features included in the knowledge expression system are not limited to the following ones. New features can be learnt and expanded in the knowledge base as required in practical applications.

Feature 1 (checking whether the frequency of the parotic noise signal is related to the ignition frequency). For a tractor with a maximum rotation speed of 2400 rpm, the ignition frequency is $f = 2400/60 \times 2 = 80$ Hz. Therefore, the rotation frequency is half the ignition frequency of the engine.

Feature 2 (peak frequency). Herein, it is defined as the maximum frequency outside the ignition frequency in the amplitude spectrum. If a same peak frequency is found both in the parotic noise and the vibration signal, this peak frequency value is considered as one of the factors for locating the noise source.

Feature 3 (correlation coefficient). It refers to the linear relationship between multiple variables, and it can often be used to quantitatively describe the degree of association between deterministic signals. The amplitude spectra of the vibration and noise signals of the engine, subsystem, and component are first obtained by Fourier transformation. The Pearson correlation coefficients between the vibration noise signal of each measuring point and the parotic noise in the cab are then calculated in the time and frequency domains. The results are further divided into different groups based on the degree of correlation. The calculation method is shown as follows:

$$r = \frac{\sum_{i=1}^{n} (X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\left(\sum_{i=1}^{n} (X_i - \overline{X})^2\right)\left(\sum_{i=1}^{n} (Y_i - \overline{Y})^2\right)}}. \quad (1)$$

The correlation between the different sets of data can be quantitatively evaluated by calculating the associated correlation coefficients. The degree of correlation is classified into four levels: Level 1 < Level 2 < Level 3 < Level 4. Level 1 represents the lowest degree of correlation, whereas Level 4 represents the highest degree of correlation. Table 1 lists the classification of each level.

Feature 4 (frequency doubling). It refers to the frequency of the engine under normal operating conditions. It is a multiple of the rotation frequency [26].

Feature 5 (loudness). It is a basic parameter representing the human ear's perception of the strength of the sound signal. It is related to both the amplitude of the sound wave and the frequency [27].

Feature 6 (sharpness). It is used to reflect the ratio of the sound component in the high-frequency band to that in the low-frequency band of a noise signal [28].

Feature 7 (roughness). It refers to the fluctuation in the sound signal in the time domain and is mainly due to the modulation of the sound signal [28].

Table 1: Classification of degree of correlation.

Correlation coefficient ρ_{xy}	Degree of correlation
±0.00~±0.30	Level 1
±0.30~±0.50	Level 2
±0.50~±0.80	Level 3
±0.80~±1.00	Level 4

4. Case Study

A case study is conducted by collecting the sound and vibration signals from the driver's cab of a tractor. Parotic noise signals are collected at the operator's position, and vibration signals are collected from different parts of the vehicle. The characteristics of the noise sound signal and sound vibration signal are matched through the ontology knowledge expression system. If the match is successful, the noise signal is considered to be related to a specific vibrating part. The exact features by which such a correlation is represented can also be deduced at the same time. To achieve this, signal processing is first performed on the collected data. Subsequently, the matching and reasoning of the data are completed using Protégé. The deduced results are compared with artificially processed signals to verify the validity and accuracy of the ontology system. Accurate information is extracted based on the test data and is used to provide guidance for subsequent noise control.

4.1. Acquisition of Sound and Vibration Signals. The test vehicle is an export-type tractor with the model number MD1204. The testing and evaluation of the vibration and noise signals received from the tractor are performed according to EU standards (Directive 2009/63/EC). Multiple measurements are taken during the test according to the statistical law, and a mean value is obtained from the test results. The obtained signals are checked for abnormality, and the abnormal signals are excluded from the results. The main objective of the noise test is to collect the parotic noise signal at the operator's position. The vibration noise testing plan is determined based on the selection standard and actual working conditions.

The signals required for the test include the parotic noise signal at the operator's position, vibration signals at the four marker point positions (named 1, 2, 3, and 4) of the engine, vibration signals at the four marker point positions (named 5, 6, 7, and 8) of the shock absorbers in the driver's cab, engine ignition frequency signal, air filter signal, muffler signal, and back-panel signal, as shown in Figures 6(a)–6(c). All the signals are collected under two working conditions, i.e., at rotation speeds of 700 and 2400 rpm.

According to the requirement of this experiment, the following features are extracted from the collected signals: the frequencies associated with the amplitude peaks (excluding the fundamental frequency in the amplitude spectrum), ignition frequency, and correlation coefficient.

4.2. Knowledge Reasoning Based on Ontology. The time-domain signals are obtained by sampling the data using the Shannon sampling theorem. Because the frequency features are more important for performing the analysis, the time-domain signals are converted to frequency-domain signals via time-to-frequency conversion. The peak frequencies in the parotic noise spectrum are compared with the corresponding characteristics of the vibration spectrum of the other vehicle parts. A correlation analysis is performed between the parotic noise and signal at different signal measurement locations in the vehicle. Because the noise signals collected at the left and right ears are in good agreement, only the noise signals at the left ear are used for the subsequent analysis.

4.2.1. Data Preprocessing. According to the standard requirement, we first check whether the sound level of the parotic noise is within the standard range. The original signal collected during the test represents only the intrinsic characteristics of the signal itself; however, when evaluating the noise signal, we are more concerned with the subjective perception of the noise by the human ear. Therefore, it is necessary to weight the sound pressure level of the noise signal. The type A weighting method, which most closely represents human hearing, is used in our study. Figures 7 and 8 show the 1/3 octave spectrum and amplitude spectrum of the type A weighted parotic noise signal, respectively, under the working condition of 2400 rpm. Here, the value of 2400 rpm is the highest speed, which is the only criterion to judge whether the parotic noise signal is up to the standard. The signal analysis at this speed is the most persuasive.

The frequency and amplitude spectrum results show that, within the approximate range of human hearing, the sound pressure level is the highest at a frequency of 315 Hz. The actual hearing experience is also the most significant at this frequency. The specific frequency points are clearly shown in the amplitude spectrum, where the highest amplitude is obtained at 349 Hz, followed by the amplitude of the fundamental frequency of the engine at 80 Hz. Considering the range of frequency in which 349 Hz is located, the main frequency contributing to the excessive sound pressure is found to be 349 Hz.

The major source of the parotic sound pressure other than the amplitude of the fundamental frequency is the frequency point at 349 Hz. The frequency characteristics of the vibration signals collected from different parts of the vehicle are examined to check whether the anomalously high amplitude is also found near the same frequency point. Taking the back panel under the working condition of 2400 rpm as an example, the vibration signal of the back panel is found to exhibit an unusually high amplitude at the same frequency point, as shown in Figure 9. This amplitude is considerably higher than that of the fundamental frequency. Based on the consistency between the vibration signal and parotic noise signal, it is preliminarily concluded that the back panel is the main vibration source of the strong parotic noise sound. Based on this method, the vibration amplitude spectrum of the part explored in this study is obtained. The frequency point with the highest amplitude other than the fundamental frequency in the amplitude spectrum is identified and recorded. Feature 2 is extracted in the test.

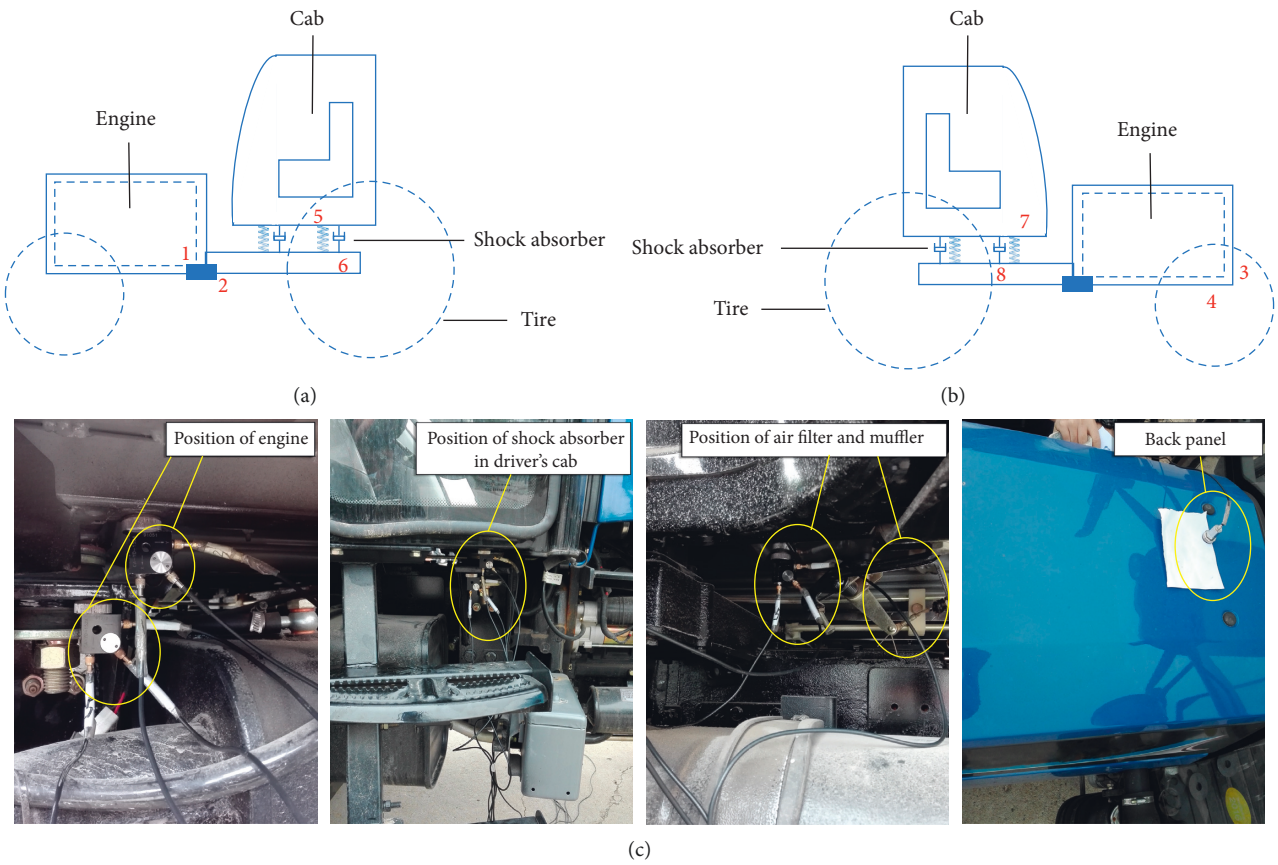

Figure 6: Noise and vibration measurement locations in a test vehicle. (a) Left view of the tractor model frame. (b) Right view of the tractor model frame. (c) Practical on-site test.

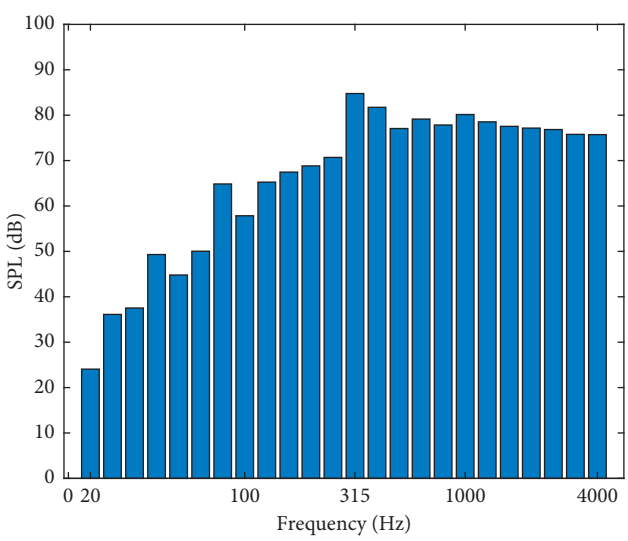

Figure 7: 1/3 octave spectrum of parotic noise sound under the working condition of 2400 rpm.

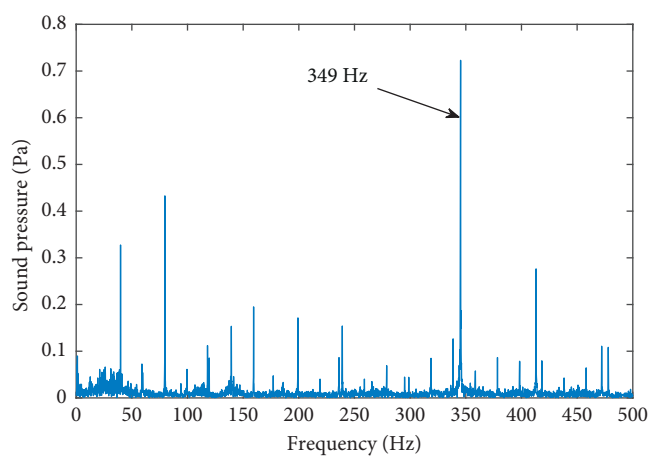

Figure 8: Amplitude spectrum of parotic noise sound under the working condition of 2400 rpm.

4.2.2. Feature Extraction. The signal features required for the experiment are extracted by following the above-mentioned data processing and correlation analysis.

Feature 1 (ignition frequency). The calculation results show that the ignition frequencies at rotation speeds of 700 and 2400 rpm are 23 and 80 Hz, respectively. The ignition frequency at the rotation speed of 2400 rpm is highly consistent with the parotic noise signal. Table 2 lists the detailed results.

Feature 2 (peak frequency). It represents the frequency with the maximum peak amplitude other than the ignition frequency in the amplitude spectrum. Based on the amplitude spectrum of the vibration signal, the

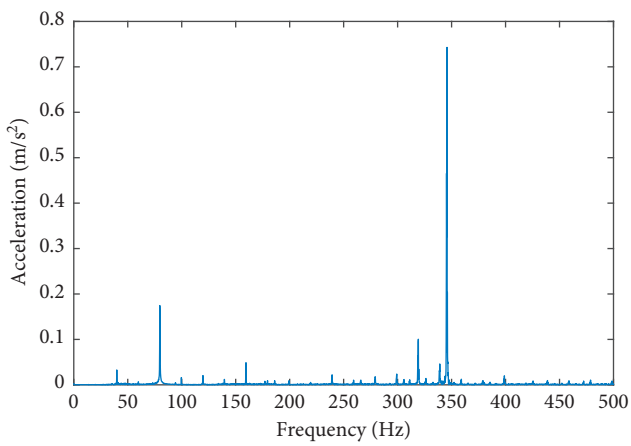

Figure 9: Amplitude spectrum of vibration at the back panel.

Table 2: Ignition frequency.

Rotation speed (rpm)	Ignition frequency (Hz)	Parotic noise frequency (Hz)
700	23	—
2400	80	80

frequency point with the highest peak in the frequency domain other than the ignition frequency amplitude is extracted and recorded, given that such a point exists. Moreover, the frequency point with the highest amplitude in the amplitude spectrum is extracted from the noise signal at the left ear. The noise signal frequency matches the vibration frequency at 349 Hz. Table 3 lists the detailed results.

Feature 3 (correlation coefficient). The correlation coefficient associated with each vibrating part is calculated and classified based on the degree of correlation. Table 4 lists the detailed results.

4.3. Knowledge Reasoning and Results. The signal feature representation is realised by editing the ontology rules, thereby establishing the relationship between the features and noise signal source. The extracted features are inputted to Protégé 5.2, and the rules are inputted to the ontology using SWRL plugins. The reasoning is performed using the Pellet inference engine. The ontology reasoning results are tabulated (Table 5), and the table indicates that the reasoning results of the features of the parotic noise signals and vibration position signals match.

(1) When the rotation speed is 700 rpm, the parotic noise signal is found to be related to the vibration signal of the back panel. Such a correlation is represented by the frequency of the peak signal in the frequency-domain signal spectrum. When the rotation speed is 2400 rpm, the parotic noise signal is found to be related to the vibration signal of the back panel. Such a correlation is also represented by the frequency of the peak signal in the frequency-domain signal spectrum.

(2) When the rotation speed is 2400 rpm, the parotic noise signal is found to be related to the ignition frequency. This correlation is identified by comparing the frequency of the peak signal in the frequency-domain signal spectrum and the ignition frequency of the engine.

(3) When the rotation speed is 700 rpm, the parotic noise signal is found to be related to the vibration signals of the machine components. These correlations are simultaneously indicated by the signal correlation. Overall, the degrees of correlation associated with the engine and cab are classified as Level 1, whereas that associated with the back panel is classified as Level 2. When the rotation speed is 2400 rpm, the parotic noise signal is also found to be related to the vibration signals of the machine components. These correlations are also indicated by the signal correlation. Overall, the degrees of correlation associated with the engine and cab are classified as Level 1, whereas that associated with the back panel is classified as Level 3.

Based on the reasoning results, we locate the noise signal source under the different working conditions using the three extracted signal features and determine the features by which the noise signal source is represented.

4.4. Improvement Program. Based on the analysis of the reasoning results, it can be preliminary determined that the back panel is the main source of vibration that causes excessive parotic noise. A structural improvement is implemented for the back panel based on the structural sensitivity analysis. The shape and thickness of the panel are adjusted following a shape and size optimisation approach, which improves the NVH performance by changing the vibration mode and increasing the stiffness of the panel. Next, the effectiveness of the proposed adjustment plan is validated by performing experimental tests.

After processing the collected noise and vibration signal data, we obtain the amplitude spectrum of the vibration signal from the back panel and the sound pressure level of the parotic noise signal before and after implementing the structural improvement of the panel, as shown in Figures 10 and 11, respectively.

5. Discussion

The ontology-based knowledge expression method proposed in this paper can be used to easily locate noise signals and select key features in the cab of agricultural machines. This method also provides a basis for resolving the noise problem in the driver's cab. Based on the results, it is found that mechanical engineers are more likely to make decisions using the ontology system, i.e., by utilising ontology knowledge and rules. The potential correlations between the parotic noise signals in the cab and the signals at other different locations are identified based on the reasoning of the actual measurement data. The identification allows us to locate the noise signal sources and determine the relevant

Table 3: Peak frequency (Hz).

Working condition (rotation speed: rpm)	Engine 1	Engine 2	Engine 3	Engine 4	In the cab 5	In the cab 6	In the cab 7	In the cab 8	Air filter	Muffler	Back panel	At operator's position Near left ear
700	349	—	500	—	349	—	349	349	—	—	349	349
2400	349	349	500	275	349	—	475	475	410	410	349	349

Table 4: Correlation coefficients.

Working condition near left ear (rotation speed: rpm)	Measuring point location 1	2	3	4	5	6	7	8	Air filter	Muffler	Back panel	Working condition for vibration (rotation speed: rpm)
700	−0.035	0.067	−0.039	0.009	0.139	−0.001	0.021	−0.032	0.201	0.281	0.432	700
2400	−0.119	0.111	−0.038	0.062	0.023	−0.068	0.015	−0.062	0.283	0.311	0.511	2400

Table 5: Ontology reasoning results.

	Engine 1	Engine 2	Engine 3	Engine 4	Cab 5	Cab 6	Cab 7	Cab 8	Air filter	Muffler	Back panel
700 rpm											
Ignition frequency											
Peak frequency	✓				✓		✓				✓
Correlation coefficients		Level 1				Level 1					Level 2
2400 rpm											
Ignition frequency		✓									
Peak frequency	✓	✓			✓						✓
Correlation coefficients		Level 1				Level 1					Level 3

Note: "✓" represents cases where outputs of ontology reasoning results are obtained, and the blank spaces indicate that no output is obtained.

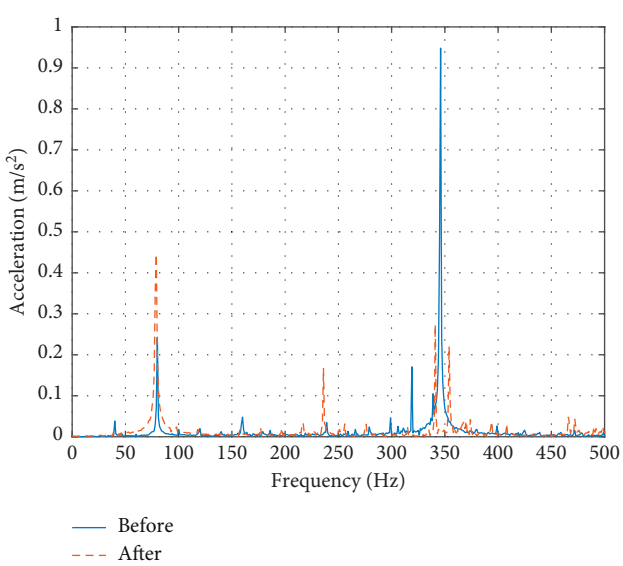

Figure 10: Vibration signals before and after performing structural optimisation.

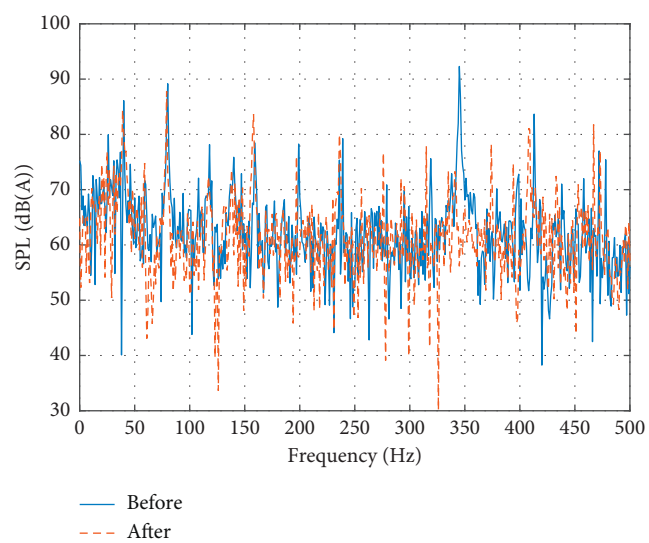

Figure 11: Contrast of parotic noise signals before and after performing structural optimisation.

features from the sources. Table 6 presents the implementation of the SWRL rules for feature extraction.

The method of locating the noise signal source based on the ontology knowledge fundamentally involves matching of the signal features based on the rules. For the case study conducted in this study, when the engine is running at 700 and 2400 rpm, Feature 2 (Table 3) of the signal collected at the operator's position and from the back panel triggers Rule 2.2. Therefore, the results reveal that the maximum peak frequency other than the fundamental frequency in the amplitude spectrum is related to the back panel. Similarly, the correlation coefficient between the signals collected from the two locations triggers Rule 3.1, which confirms that the parotic noise at the operator's position is related to the back

Table 6: Implementation of SWRL rules for feature extraction.

Rule 1	*Feature 1 (ignition frequency check)* Checking whether the parotic noise signal is related to the ignition frequency Input the ignition frequency (specific numerical value); if the rule matches, it is inferred that the parotic noise signals are related to a specific vibrating part. The feature of this correlation is represented by the "ignition frequency"
Rule 2	*Feature 2 (peak frequency check in the noise source)* Checking whether the peak frequencies in the noise source correspond to the peak frequencies in the vibration source *Rule 2.1 (specially for/applies to the engine and cab)* *Rule 2.2 (specially for/applies to the air filter, muffler, and back panel)* Input the peak frequency (specific numerical value); if the rule matches, it is inferred that the parotic noise signals are related to a specific vibrating part. The feature of this correlation is represented by the "peak frequency"
Rule 3	*Feature 3 (correlation check and identification)* Calculating the correlation between the parotic noise signal and the location signal of the tractor and identifying the locations exhibiting a specific correlation (four different degrees of correlation) *Rule 3.1 (determining the degree of correlation)* Input the correlation coefficient (specific numerical value); if the rule matches, it is inferred that the parotic noise signals are related to a certain position. The feature of this correlation is represented by the "correlation" *Rule 3.2 (determining the degree of correlation and the locations)* Rule 3.2 is divided into four rules corresponding to Levels 1, 2, 3, and 4 Rule 3.2.1 (applies to Level 1) Rule 3.2.2 (applies to Level 2) Rule 3.2.3 (applies to Level 3) Rule 3.2.4 (applies to Level 4) Input the correlation coefficient (specific numerical value); if the rule matches, it is inferred that the parotic noise signals are related to a specific vibrating part. The feature of this correlation is represented by the correlation. The degree of correlation is Level 1, 2, 3, or 4

panel. Under both the rotating speed conditions, the correlation coefficients between the parotic noise signal at the operator's position and the vibration signal from the back panel trigger Rule 3.1, Rule 3.2.2, and Rule 3.2.3. The degrees of correlation under the working conditions of 700 and 2400 rpm are classified as Level 2 and Level 3, respectively; these levels represent a more significant correlation than the other levels. When the rotation speed is 2400 rpm, Features 1, 2, and 3 of the parotic signals collected near the operator's position and the vibration signal from the engine trigger Rule 1, Rule 2.1, and Rule 3. The results show that the parotic noise signal is related to the engine ignition frequency. This correlation is represented by two features, i.e. the peak frequency in the frequency domain of the signal and the engine ignition frequency. These two features satisfy Rule 3.1 and Rule 3.2.1, and the degree of correlation is classified as Level 1.

Figure 8 shows that the 349 Hz component is the main frequency of the parotic noise signal. Table 3 indicates that the 349 Hz component appears in the vibration signals of only the engine, cab, and back panel. However, the correlation coefficients in Table 4 illustrate that the vibration signal of the back panel has the largest correlation with the parotic noise signal; the correlation coefficients at the speeds of 700 and 2400 rpm are 0.432 and 0.511, respectively. Considering the rank range of the correlation coefficient, the degree of correlation of the back panel is classified as Levels 2 and 3. However, the correlation coefficients of the engine and cab are classified as only Level 1. Therefore, from manual calculations and analysis, it is concluded that the back panel is a major contributor to the parotic noise signal. Summarising the analysis findings, the back panel is preliminarily confirmed to be the main vibration source component, causing a high parotic signal noise. In terms of identifying the vibration source, the testing data are analysed using spectrum correlation, which helps us to obtain the main vibration frequency features of the structural component. These vibration frequencies are compared with the noise sound signal, revealing a consistent frequency point at 349 Hz in both the vibration signal from the back panel and the parotic noise signal. Therefore, the main source of the noise is identified to be the back panel. Simultaneously, the inference results of ontology are viewed. It can be seen intuitively from Table 5 that when the rotation speeds are 700 and 2400 rpm, the back panel is shown to be related to the peak frequency and the correlation coefficients are classified as Levels 2 and 3; the coefficients at both the speeds for the back panel are higher than those for other vibration test locations. This result is consistent with the finding obtained using the ontology-based method.

Subsequently, the back panel is improved based on the experimental results. Specifically, the stiffness and abnormal vibration of the structure are enhanced and reduced, respectively, by modifying the structural shape and thickness of the back panel. Figure 10 shows the results associated with the improved back panel, where the acceleration peak at 349 Hz in the vibration signal of the back panel is considerably reduced. A relatively large peak emerges at a different frequency, i.e., 250 Hz. Figure 11 shows that the sound pressure level of the parotic noise is significantly reduced at the frequency of 349 Hz. However, there was no significant change in the other frequencies. These findings show that the structural improvement is effective and that the ontology-based noise source identification and analysis method proposed in this study is accurate and effective.

This study proposes a new method that integrates all the relevant knowledge in the field of NVH for agricultural

machine cabs. Based on this method, we establish a complete decision-making and problem-solving framework that can help mechanical engineers deal with vibration and noise problems more quickly and easily. The main aspect of the proposed method is the construction of a framework to express the knowledge in the specific field using ontology. This includes establishing an ontology model, performing reasoning based on the corresponding rules, and expressing the knowledge and associated correlations in the specific field. This approach represents a new manner of functioning, as indicated by the following advantages:

(1) The accuracy of the experimental results is guaranteed. Through continuous improvement and extension of the knowledge base and rule sets of the ontology model, a large amount of testing information can be incorporated and the knowledge of the mutual correlation between the knowledge base and rule sets can be improved. This extension is similar to the accumulation of experience. The more the ontology is used, the greater will be its accuracy.

(2) The work efficiency is improved. Complex experimental data can be sorted and analysed rapidly.

(3) Manpower and time are saved. The ontology method is implemented by computer based on the internal logic of ontology. It is faster than manual processing.

(4) Information sharing and reuse can be implemented. Ontology can be used as a powerful tool to sort, summarise, and refine prior procedural knowledge of NVH diagnosis to overcome the difficulty in information sharing and reuse in this field.

The above advantages will allow mechanical engineers to identify and analyse the noise source considerably more efficiently and conveniently by integrating all the relevant information. The proposed method can also support any requirements of subsequent improvements.

6. Conclusion

In this study, we developed an ontology knowledge expression model for agricultural machines in the field of NVH based on the rules of ontology and the SWRL and provided an extensible framework for sharing information and noise diagnosis knowledge in the field. Based on a case study, we constructed an initial NVH ontology knowledge base and rule sets incorporating well-defined SWRL rules, which were used as a "feature analysis tool." By expressing the knowledge in the specific field and performing corresponding ontology reasoning, the knowledge base and rule sets can be used to extract intrinsic correlations between signal features, locate signal sources, and identify the associated signal features. It has also been demonstrated in our case study that the proposed method can support a common understanding of the knowledge in the field of NVH, resolve the problems of integrating and sharing knowledge in the field, tackle the interoperability problems between noise diagnosis knowledge models, and furthermore realise an intelligent noise diagnosis expert system to a certain extent. Thus, the complex experimental data can be sorted and analysed rapidly, thereby significantly improving the working efficiency. The proposed method is of certain theoretical and practical significance for solving the noise and vibration problems in agricultural machine cabs. It also provides a new perspective for reducing the vibration and noise in tractors.

This study is a preliminary work to analyse the noise source of the cab with the ontology knowledge expression model. It provides a guideline for vibration and noise control of a tractor. While the purpose of the approach based on the developed ontology is to improve the decision-making process, which, in this case, is a structure with a signal feature extraction frame, the model can be extended to other frames, not limited by features. In the future work, one can develop and improve the ontology knowledge expression model gradually and further improve the automation ability by enhancing the interactions between different models. From the perspective of the entire field of NVH, the ontology knowledge expression model can be extended to incorporate more practical aspects based on the knowledge and experience of experts in the field, such as more in-depth analysis of the noise source and decision-making in noise control and reduction. The continuous improvement in the knowledge base and rule set of the ontology model can help incorporate more amount of NVH testing information and knowledge expression of their mutual correlation. This will allow the design system to perform reasoning that simulates the thinking process of the experts in the field and will assist engineers to perform different experimental research and analysis. By combining the complex experimental design process with the advanced computer technology, we can establish a knowledge-based NVH analysis design system and ultimately establish a consistent information model that is compatible with the NVH problem-solving process.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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