

Lumped Element Dynamic Modeling for Vibrotactile Material Recognition in Robotic Grasping

*Modal Analysis and Transmissibility Interpretation of a Vibrotactile Robotic
Gripper System*

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Abstract

In this thesis the dynamic behavior of a vibrotactile robotic gripper system through the analysis of vibration transmissibility was demonstrated by focusing on understanding the structure of experimentally measured responses. A two finger gripper was used for experimental measurements where a vibration motor used as a source of excitation on one finger of the gripper, and the vibration response is measured on the opposite finger. This gives a transmissibility-based representation of the system dynamics. For the experimental modal analysis, both Python and MATLAB are used which gives the validation of the results. To extract physically meaningful modal features, feasible frequency regions are identified using coherence function. The physical characteristics of the system are validated by a reduced-order lumped mass-spring-damper model in COMSOL Multiphysics and the comparison between the numerical response and experimental results is done along with parameter tuning to better match the results.

Chapter 1

Introduction

1.1 Background

1.1.1 Robotic Manipulation and Tactile Sensing

Tactile information is a necessary factor in dexterous robotic manipulation since it provides necessary contact information such as material identification and stable grasp control which helps robotic hands interact with surrounding objects effectively [1]. Modern tactile sensors enhance perception in robots with the interaction-related information such as surface texture, applied pressure, and geometry of object. These parameters are essential that let robots adapt to uncertainties during robotic manipulation tasks [2]. Because of the interaction-rich information provided by the tactile sensing, researchers have experimented a wide range of tactile sensing methods including capacitive, piezoelectric, piezo resistive, optical tactile sensing, acoustic and vibration-based techniques. Among these, acoustic and vibration-based techniques have achieved popularity in modern tactile-based robotic manipulation.

Researchers have widely used vision-based sensing for robotic manipulation tasks since it can show the global geometry of objects using computer vision. Vision-based tactile sensing (VBTS) can provide contact information using cameras and a single sensing modality, which is not sufficient for understanding comprehensive environmental perception by robots [2], [3]. Researchers used camera-based sensors to get high-resolution tactile data and 3D reconstructions of contact surfaces for object pose estimation, collision detection, and surface feature identification [4]. These methods are limited to visual feedback, and they can fail in situations where the visual feedback is missing, and they often fail to provide object dynamic information such as texture, stiffness, or contact dynamics [1], [4].

Additionally, many vision-based techniques need to have prior knowledge of the target, which requires different algorithms to be designed for analyzing different scenes and objects, and their performance can also be affected by illumination variations, occlusions, and complex backgrounds [3]. In vision-based perception, objects can sometimes be partially visible or completely hidden or occluded by other environmental objects during interaction

with a robotic manipulator [5]. Furthermore, vision systems cannot infer intrinsic properties of material such as stiffness, damping, friction, and other internal properties which play a key role in object structure understanding during physical contacts [6]. These gaps in vision-based systems limit their performance in real-world perception tasks. The limitations in these techniques lead us to use tactile sensing, which, through direct physical contact, can enhance robotic perception by providing information about the properties of the contact object [7].

1.1.2 Vibration-based Tactile Sensing

Recent studies have shown that vibrations observed from contact interactions can hold necessary information about object properties and internal characteristics. For example, a study showed high-frequency vibration signals during sliding contact can provide specific features associated with object texture and material composition [6]. Through experiments, the authors demonstrated that the analysis of vibrations from contact scenes can enhance object recognition. They achieved the classification accuracy of 97.6% across multiple objects [6]. Similarly, in dynamic tactile sensing, active vibrations generated from active exploration have been used to achieve 90% accuracy in surface texture recognition [8]. Other studies have proved that internal mechanical properties such as stiffness, viscosity, and friction can be revealed through vibration responses during contact with object classification accuracy of 98.18% [9]. These findings successfully demonstrate that mechanical vibrations from the active interaction framework can give discriminative information for robust object recognition and material identification.

In addition, more informative sensory signals can be achieved through actively generated vibrations as compared to passive vibration responses. Active vibration sensing is achieved by intentionally exciting the object and measuring the vibration responses generated from the intentional excitation. This enhances object recognition performance in robotic manipulators [7]. Vibration-based material discrimination experiments were carried out for optimal material discrimination, where they used controlled active vibrations to achieve the classification accuracies of above 90% in material classification [10]. These experiments show the importance and the vital role of active vibrations in inferring meaningful features of contact objects for optimal perception frameworks in robotic manipulators.

Acoustic sensing has also been used as an alternative approach for getting useful information about object properties such as material composition, internal structure, and container contents [11]. In this method, the researchers analyzed sound waves generated during interaction, like tapping and shaking objects, and they found from this analysis that one can get necessary object features from acoustic vibrations [11]. However, many acoustic sensing approaches using microphones can suffer from environmental noise and nearby distractions and hence require controlled experimental conditions [11]. Acoustic sensing approaches can also be affected by interference caused by robot motor noise and other environmental sounds, which make them unreliable for their application in real-time perception frameworks during manipulation tasks [12]. Therefore, the lack of sufficient

tactile information is considered to be the major hindrance or limiting gap in robotic performance to achieve fully dexterous manipulation by understanding object dynamic properties [1].

Due to the limitations in the above-mentioned techniques, our approach considers directly measuring mechanical vibrations through physical contact. This can provide a deeper analysis of object dynamics. Mechanical vibration response can be used to estimate intrinsic material properties such as stiffness, damping, and structural response. Therefore, active vibrotactile sensing provides a promising solution for accurate material identification and object perception in robotic manipulation systems.

1.1.3 Role of Mechanical Vibrations in Material Identification

Mechanical vibrations during contact interaction can provide important information about the physical properties of materials. When a structure gets excited, vibrations are generated, and these vibrations are distinctive in nature in the sense that they depend on the intrinsic parameters such as mass, stiffness, and damping of the contact object. This distinctive nature of vibrations carries the dynamic behavior of the system [13].

Since the active vibration signals mimic the dynamic response of the objects, they can disclose internal mechanical features of materials during the contact [13]. To analyze these dynamic properties through vibrational response, many sensing techniques used controlled excitation and sensors such as accelerometers to detect the resulting vibrational response [14]. Similarly, engineering systems have been using vibration analysis for a long time to monitor structural conditions by observing changes in vibration behavior to analyze variations in system properties or operating conditions [15].

In robotics, mechanical contact during robotic interaction with objects generates vibrations that carry signatures of object properties. These vibrations can come from the physical contacts such as force, deformation, and friction between contacting surfaces [16]. Vibrational responses can infer object characteristics, including stiffness, damping, and friction behavior, due to their dependency on intrinsic mechanical characteristics [9].

From experimental studies, it is clearly demonstrated that accurate object recognition can be achieved from the analysis of the active vibrations. A study that estimated the mechanical properties from vibration and force signals achieved 98.18% recognition accuracy [9]. Furthermore, internal material variations or structural irregularities within objects are determined from the generated vibrations through squeezing or contact interactions [16].

Dynamic tactile exploration further highlights the role of vibrations in material perception. Frictional interactions produce vibration signals when a sensor or robotic fingertip slides across a surface. The frequency characteristics of these vibrations depend on surface properties such as roughness and texture [8]. The surface textures classified using these friction-induced vibrations gave the recognition rates above 90% by extracting the discriminative features of the surface textures [8].

Similarly, studies on tactile perception further demonstrate that material properties, including surface roughness and hardness, can be estimated by analysing vibration spectra

obtained during sliding interaction using frequency-domain techniques specifically using Fast Fourier Transform (FFT) [17]. From these findings, we can get to know the importance of active vibrations in providing valuable information about surface characteristics.

Active vibration excitation has also been widely used to investigate material properties. In such systems, controlled vibrations from one side, say the transmitter side, are injected into a structure, and the transmitted vibrational response is measured using sensors on the other side, say the receiver side [10].

Depending on their mechanical properties, different materials give different vibration responses by modifying the vibration path. Therefore, each modification gives a distinctive feature related to the contact material, and this information is used for successful material discrimination [10]. The vibration-based sensing experiments performed in [10] obtained the material classification accuracies greater than 90% using vibration and resonance responses. Another study [14] also showed that controlled vibration responses when analyzed in the frequency domain, extract information such as material stiffness and other structural characteristics.

Similar experiments have been carried out in [18] for enhanced object recognition purposes, where vibrations are generated from one side, similar to [10], and found that the transmitted vibration signal was affected by mechanical properties such as stiffness, damping, density, and mass. From the resulting vibration spectrum, the authors found that each material modified vibration signals in its own unique way and hence can hold unique signatures for unique object identification [18]. The accuracies obtained in this study exceed 92.5% in distinguishing objects of different materials. These results confirm that intrinsic material characteristics can be obtained from the active vibration signals.

Vibration signals generated during interactions provide additional information about object properties while propagating through solid materials. Vibrations propagate through the structure; an interaction with a touch can be detected using sensors placed at different locations [19]. The observed vibration responses depend on material characteristics and other factors such as vibration frequency and propagation distance [19]. These propagation characteristics form unique vibration patterns associated with object properties by going through different interaction effects such as reflection, diffraction, and interference [19]. This behavior makes vibration-based sensing methods capable of inferring object characteristics even without the sensors placed directly at the interaction point [20].

Another advantage of vibration-based tactile sensing has been discussed in [20], where the researchers tested the ability of vibration sensing to transmit information through grasped objects or tools. For this purpose, vibrations have been generated at a contact point, and the response of vibrations propagated through rigid structures has been detected at remote sensing locations [20]. Consequently, they came up with the expected system behaviour. This aspect can extend the sensing range of the system, and, through this practice, robotic systems can detect contact events beyond the exact location of the tactile sensor [20]. Additionally, the authors [20] also mentioned that the accurate location of contact points along rigid structures can be determined with an error below 1cm using vibration response that travelled through the material. Furthermore, this research

also confirmed that higher sampling rates used can increase the ability to detain more meaningful vibration patterns for optimal perception tasks in robotics [20].

Active vibrotactile systems further use purely mechanical vibrations for robotic perception, where vibrations are actively generated within the system, and the resulting patterns are estimated to see the variations during object interaction [21]. These systems emphasized the mechanical nature or physics behind the system and the contact object by considering mass-spring-damper models, where the sensor and object interaction modifies the resonance characteristics of the system [21]. In this study, contact events are determined from the change in amplitude of vibration and the resonance frequency. This study also confirmed that even highly sensitive light events can be detected from these vibration patterns with an estimated signal-to-noise ratio of 18, as compared to 8 in the case of using traditional force-sensing techniques.

Research on human tactile perception also confirmed the importance of vibrations in material identification. Mechanoreceptors in human skin are highly sensitive to vibrations, specifically, they respond strongly in 40 - 800 Hz frequency range [22]. Humans detect fine surface characteristics through their fingertips since it's the most sensitive area with sensitivity around 250 Hz [22]. When a finger slides across a material surface, friction and deformation happen, and because of this, vibration signals are generated, which uphold information about texture, roughness, and hardness [17]. Similarly, vibration signals are also used for detecting fabric characteristics, where the generated vibrations during sliding interactions with fabrics unveiled fabric material properties such as softness, fineness, and the success rates for material discrimination observed to be more than 90% [23].

Overall, from the above-mentioned findings, we can demonstrate that mechanical vibrations observed during physical contact contain meaningful patterns about the surface as well as the interior properties of materials. Since vibration signals rely directly on mechanical parameters such as stiffness, density, damping, frictional characteristics, as well as structural dynamics, vibration-based techniques offer a physics-based approach for efficient material identification. Because of these characteristics, vibration-based sensing becomes particularly useful for robust manipulation systems, where controlled mechanical vibrations and their analysis can infer the complex and dynamic behavior of grasped objects.

1.2 Problem Statement

Robotic manipulation systems depend increasingly on physical interaction tactile feedback for obtaining information about objects. Vibration-based tactile sensing among various sensing techniques is currently considered to be a promising methodology for dynamic behaviour information extraction through contact interaction analysis. Mechanical vibrations when propagate through a robotic gripper from one side through the contact object to the other side, give valuable feedback about the mechanical dynamics of the system.

However, easy said than done, the interpretation of these vibrations is not straightforward because the measured vibration response in the end effector gets affected by a number

of factors which include but not limited to the structural dynamics of the gripper fingers, the mechanical dynamics of the contact interface as well as the fingers coupling mechanism. Because of these internal factors, the direct interpretation of complex resonance and anti-resonance patterns in the measured vibration spectrum becomes difficult.

The experimental setup used for this study contains a vibration motor which excites one finger of the robotic gripper. Two ADXL335 accelerometers are mounted on both fingers to measure the vibration responses. In the void case, vibrations are measured from both fingers, whereas in the contact case the response is measured from the receiving finger through the contacted object.

We are interested in describing how vibrations propagate from the transmitting finger to the receiving finger through the contact object. This phenomenon can be represented using the transmissibility function:

$$H(f) = \frac{a_{Rx}(f)}{a_{Tx}(f)} \quad (1.1)$$

where $a_{Tx}(f)$ represents the acceleration spectrum measured at the transmitting finger and $a_{Rx}(f)$ represents the acceleration spectrum measured at the receiving finger.

Therefore, the transmissibility function $H(f)$ becomes the main quantity of interest in this study. Even though the transmissibility spectra are obtained from experimental measurements, the physical interpretation of the estimated peaks, dips, and phase variations remains unclear.

Without a clear picture of the dynamic mechanism that holds these necessary spectral features in its core, one cannot fully utilize the performance of vibration-based tactile sensing techniques for robotic perception tasks. It is particularly important to know which spectral features are associated with real dynamic modes of the system and how the interacting object can change the behaviour of these modes.

Therefore, to utilize the benefits of current promising tactile sensing for robotic manipulation which is vibration-based sensing, we need to have a systematic approach that can interpret the measured vibration transmissibility of the robotic end effector or gripper to identify the dominant dynamic modes which provide a clear picture of the system response. The possible approach to explain the main dynamic features of the system and understand how the vibration response gets modified by contact objects is to combine modal analysis of the experimental spectra with a simplified physical modelling, such as a simple mass-spring-damper system.

1.3 Research Objectives

The main objective of this research is to use model analysis and reduced-order dynamic modelling for the clear interpretation of vibration transmissibility measured in a tactile robotic gripper for object recognition and material identification.

The specific objectives to handle this task are given below:

1. To perform analysis of the experimental vibration transmissibility spectra of the robotic gripper, including magnitude, phase, and coherence, in both the void case and the contact case.
2. To use modal analysis of the experimentally achieved spectra for the identification of the dominant dynamic modes which give the clear picture of the vibration response in an organized form.
3. To build a simple reduced-order dynamic model of the experimental setup, which is a two-finger robotic gripper represented by a lumped mass-spring-damper system, to capture the essential mechanical properties of the system.
4. To compare the experimentally observed modal features by implementing the proposed lumped mass-spring-damper model in COMSOL Multiphysics and computing its eigenmodes and frequency response.
5. To determine the changes in vibration transmissibility by observing how the gripper-object interaction modifies the system dynamics to provide a clear physical interpretation of the measured vibrations.

Chapter 2

Methodology

2.1 Overview

The aim of this study is to observe the dynamic mechanism of a two-finger robotic gripper by understanding the vibration transmissibility that explains the system's vibration response. The methodology focuses on identifying dominant system modes by applying spectral analysis to the experimentally obtained system response and building a simplified physical model to verify these observations.

The structural workflow of the methodology involves:

1. Analysis of experimentally obtained vibrational signals to get clear transmissibility spectra that can include magnitude, phase, and coherence of the response.
2. Identifying the dominant frequency regions from the spectra that represent the reliability of physical meaning behind the system to identify system characteristics, including resonance, anti-resonance, and phase translations.
3. Using modal analysis to observe the structure of the measured response by determining the vibration modes.
4. Developing a simplified reduced-order dynamic model of the system in COMSOL by representing it as a lumped mass–spring–damper system and computing eigen frequencies to compare the results with experimental measurements and observations.
5. Finally, analysing the effect of object contact on the system dynamics with the help of contact parameters to observe the way it modifies the vibration response of the system.

This section describes a physics-based framework, an experimental dataset, and the modal analysis for the interpretation of vibration transmissibility in a robotic gripper.

The primary intention is to understand the propagation of vibrations, making the dynamics of the system, and determining the way the dynamic response of the setup

is structured, which can be estimated specifically from the dominant modes hidden in vibration spectra.

Since it is difficult to fit a complex model representing all the components and parts of the experimental setup directly, the proposed methodology uses a simplified reduced-order model, which only includes both fingers' bone and tissue parts.

Model analysis can describe the dynamics of a system by interpreting natural frequencies, damping, and mode shapes [1], and it is used as a key technique to analyze the experimental data for the determination of the physical behavior of the system. The superposition of all vibration modes describes the overall behavior of the system [2].

2.2 Experimental Setup

The experimental setup explains a robotic gripper that involves two fingers with a source of vibration excitation and sensors. One finger of the gripper is represented as the transmitting side of the finger, which has been excited by a vibromotor to generate active vibrations, and the opposite finger acts as a receiving finger to measure vibrational response.

The transmitting finger, in this configuration, is denoted as Tx, and the receiving finger is denoted as Rx. The vibrations that are generated through the excitation of the transmitting finger using a motor travel through the mechanical structure of the gripper and pass through the contact object interface before reaching the receiving finger. Therefore, these vibrations can represent the dynamic properties of the overall system when measured at the receiving side.

To better analyse the transmission path of these vibrations, an important function called the transmissibility function is used. This function represents the ratio of the acceleration measured at the receiving finger to the acceleration at the transmitting finger.

The transmissibility function, in mathematical terms, is represented by the following expression.

$$H(f) = \frac{a_{Rx}(f)}{a_{Tx}(f)} \quad (2.1)$$

where

- $a_{Rx}(f)$ is the acceleration on the receiving finger, and
- $a_{Tx}(f)$ is the acceleration spectrum measured at the transmitting finger.

2.3 Experimental Modal Analysis

Modal analysis is a typical starting point for a dynamic analysis. It is the most fundamental of all dynamic analysis types; essentially, it looks for the natural modes (frequencies) of a structure. All structures have natural frequencies, and it is the most important feature

of the structure, especially in dynamics. On the basis of their nature, the structures can vibrate fast or can be slow.

The most important question is, why is knowing natural frequencies important? What information can we collect from natural frequencies of a structure? By knowing the natural frequencies of structures, we can infer the dynamic features of a structure, and this information can help us understand more complex behaviour, and more complex dynamic simulations are based on natural frequencies.

Since we are aware of the importance of the knowledge about natural frequencies, finding the natural frequencies and mode shapes of a structure is an essential research question in this case. The first answer is through modal analysis.

From the definition of the transmissibility function, we realize that the experimental dataset for Tx and Rx consists of acceleration signals represented in the time domain that need to be converted to the frequency domain for better modal interpretation.

From the studies on modal analysis, it is shown that frequency-domain representations, such as frequency response functions, can better describe experimental modal analysis to identify the dominant system characteristics using measured data [1]. Therefore, for the analysis of vibration transmission to infer system dynamics, the signals have been represented in the frequency domain.

2.3.1 Spectral Analysis of Experimental Data

Spectral analysis is the most common method in data analysis, used across various data acquisition fields to measure the power spectrum at different frequencies. It is an essential time-series analysis method that extracts power, frequency, and other important signal characteristics by estimating the signal's power spectrum from its time-domain representation in terms of its frequency content.

Spectral analysis specifically answers questions like which frequencies are present in the signal and how strong each frequency component is. Its mathematical foundation goes back to Fourier theory, which explains an essential method of decomposing a time-domain signal into the convolution of its sinusoidal components: sines and cosines.

This way, spectral analysis applies in most natural and artificial processes to describe the hidden periodicities, vibrational responses, or oscillatory behaviour by representing the time-domain signals in the frequency domain. This method is significantly used in physics to identify vibrational modes in mechanical systems to describe the physical dynamics of systems.

The analysis of the vibration responses is done by processing the recorded signals in the frequency domain. The estimation of spectral analysis functions, such as power spectral density, cross spectra, and transmissibility, is performed using signal processing techniques in Python.

Using this analysis, the key frequency bands are identified, specifically focusing on the region where coherence is sufficiently high. These frequency regions represent real spectral features of the response rather than noise and artefacts. These features give clear direction for further steps of modal interpretation.

2.3.1.1 Auto-Spectral Densities

The power spectral densities (PSD) are defined as:

$$S_{xx}(f) = E[|X(f)|^2], \quad S_{yy}(f) = E[|Y(f)|^2] \quad (2.2)$$

These functions describe how vibrational energy is distributed across frequencies at the transmitting and receiving locations.

2.3.1.2 Cross-Spectral Density (CSD)

The cross-spectral analysis extends spectral analysis to two-time series (e.g., $x(t)$ and $y(t)$). From the power spectrum of a single signal, we get information about the distribution of its variance in different frequency regions, and from the cross-spectrum, we can get to know how two vibrational signals are correlated in the frequency domain.

Therefore, the cross-spectral density between two signals, say $x(t)$ and $y(t)$, is represented by the following equation.

$$S_{xy}(f) = \lim_{T \rightarrow \infty} \frac{1}{T} E[X_T(f)Y_T^*(f)] \quad (2.3)$$

where:

- $X_T(f)$ and $Y_T(f)$ are known to be the Fourier transforms of truncated signals,
- The asterisk $*$ in the equation is a complex conjugate,
- $E[\cdot]$ is called the expectation operator

Since the CSD is complex, it can represent both amplitude and phase information, which is the phase between excitation and response. These features of the CSD can be used as the basis to identify resonant behaviour. And from theories and experimentation on spectral analysis, it is evident that using frequency domain representations, including CSD and FRF (Frequency Response Function), served as the fundamental tools for modal properties description from the vibrational response [1].

2.3.1.3 Spectral Estimation Using Welch Method

Welch's method, also commonly known as the periodogram method, is used to estimate spectral quantities, particularly to determine the power spectral densities.

This method is essentially popular due to its capability to reduce variance and noise in the estimated power spectra, which is often desired to get a smoother power spectrum. It improves the Signal-to-Noise (SNR) ratio by performing segmentation and averaging of periodograms of a time series, which ensures the efficient estimation of power spectra against system or surrounding noise.

2.3.1.4 Coherence Function

The coherence function is used to determine the strength of the linear relationship between the two signals, in our case, the degree of relationship between the transmitting and receiving signals or input and output signals at each frequency.

$$\gamma_{xy}^2(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f) S_{yy}(f)} \quad (2.4)$$

where,

- $S_{xx}(f)$ and $S_{yy}(f)$ are known as auto-spectral densities (that represent power spectra) of two signals $x(t)$ and $y(t)$,
- $S_{xy}(f)$ is the cross-spectral density

Conditions and Interpretation:

$$0 \leq \gamma_{xy}^2(f) \leq 1 \quad (2.5)$$

From the coherence function estimation, we know if the system response is linear, non-linear, or partially coherent.

- If $\gamma_{xy}^2(f) = 1$, it means the input and output show a perfect linear relationship at frequency f
- If $\gamma_{xy}^2(f) = 0$, it means non-linear degree
- The intermediate values between 0 and 1 mean the signals are partially coherent

High coherence means the measured response contains the system dynamics, and on the other hand, when the coherence is low, it indicates a non-linear relationship or noise. The effectiveness of modal analysis and estimation can be affected by the system's operational conditions or environmental factors [3].

2.3.1.5 Phase Spectrum

The phase shift between two signals as a function of frequency is represented by the phase spectrum, which is described by the following equation:

$$\phi_{xy}(f) = \arg [S_{xy}(f)] \quad (2.6)$$

The phase spectrum is used to represent average time delay between input signal and output signal at each frequency which can be determined by taking average over cross-spectral density function.

Conditions and Interpretation:

- If $\phi_{xy}(f) = 0$, it means the signals are in-phase at that frequency
- A positive phase ($\phi_{xy}(f) > 0$) means that $x(t)$ leads $y(t)$,
- A negative phase ($\phi_{xy}(f) < 0$) means $y(t)$ leads $x(t)$.

2.3.1.6 Transfer Function Estimation

The transfer function $H(f)$ explains how input $x(t)$ is transformed into output $y(t)$ in the frequency domain:

$$H(f) = \frac{S_{xy}(f)}{S_{xx}(f)} \quad (2.7)$$

where:

- $S_{xy}(f)$ is the cross-spectral density, which describes the correlation between two signals at each frequency component
- $S_{xx}(f)$ is the input auto-spectral density of the input signal, which describes the distribution of the input signal's power across the spectrum
- $|H(f)|$ is the gain at frequency f , which describes whether the input signal is amplified or attenuated by the system at that frequency
- $\arg(H(f))$ is the phase shift introduced by the system at frequency f , which describes the condition of the output signal relative to the input, meaning whether the output signal is delayed or advanced as compared to the input signal.

The transfer function is also known as the Frequency Response Function (FRF), which helps in experimental modal analysis to identify modal parameters, including natural frequencies, damping ratios, and mode shapes of the system. The resonant frequencies or modes can be identified from the peaks provided by $|H(f)|$, and other system characteristics such as stiffness, damping, and mass contributions can be explained by the shape of the transfer function.

2.4 Coherence-Based Frequency Band Selection

A reliable modal identification demands considering only those frequency regions for analysis that describe a high coherence function value. The magnitude-squared coherence function between input and output signals is given as:

$$\gamma_{xy}^2(f) > \gamma_{thr}, \quad \gamma_{thr} \approx 0.6 \quad (2.8)$$

This defines the coherence band, within which the system response is physically meaningful.

The system response is physically meaningful, and the input and output signals are consistent when the system follows the criterion defined by the magnitude-squared coherence function.

The coherence-based selection method is used for the following reasons:

- Coherence-band selection can reduce disturbances from the environment and noise
- It helps to eliminate unnecessary peaks from the response that do not contribute to the system behavior
- It increases the transfer function accuracy and helps in better modal fitting

Furthermore, unreliable frequency regions can be eliminated by the application of a threshold, which is set to 0.6 in most common applications. This step is essential in experimental modal analysis to tackle imperfections in excitation, sensor limitations, and other external jerks that can affect the response quality. If we don't restrict the analysis to high-coherence regions, it can lead to misinterpreting the noise as structural dynamics. With this filtering step, the actual system behavior is obtained by retaining only the dominant frequencies of the system.

2.5 Finding System Modes

After the coherence-based band selection, the next step is to search for system modes in the coherence band, which further involves two steps: peak detection and filtering.

2.5.1 Peak Detection

Peaks in the magnitude of the cross-spectral density ($|S_{xy}(f)|$) significantly describe resonance behavior and corresponding potential natural frequencies. These frequencies, due to resonance effects, represent amplified vibration response of the system [1].

2.5.2 Coherence Filtering

Coherence filtering means selecting only those frequency components that are useful. This is done by ensuring that the input and output signals are correlated. This correlated region is what describes a meaningful response for the system.

Therefore, through coherence filtering, only the coherence region peaks are considered to be physically meaningful.

$$\gamma_{xy}^2(f_i) > \gamma_{thr} \quad (2.9)$$

where $\gamma_{xy}^2(f)$ is the magnitude-squared coherence between the input and output signals, and γ_{thr} is a predefined threshold value.

Since low coherence frequencies indicate weak or non-linear relationships between the signals, they must be ignored. Therefore, the overall system response can be defined by the combination of all the estimated modes, where each mode corresponds to a specific type of vibration that represents a specific dynamic behavior [2].

2.6 Reduced-Order Modeling

After identifying experimental modes using spectral analysis, a low-order mass-spring-damper model was built to interpret the dominant modes identified in the system. The actual experimental setup representing each component of the robotic gripper including both Tx and Rx components is reduced to a simplified mass spring damper model shown in Fig 2.2 in COMSOL to check whether a simple model of COMSOL can reproduce the same experimentally obtained modes rather than modeling the whole system which leads to complexity in explaining real dynamics of the system in the first place.

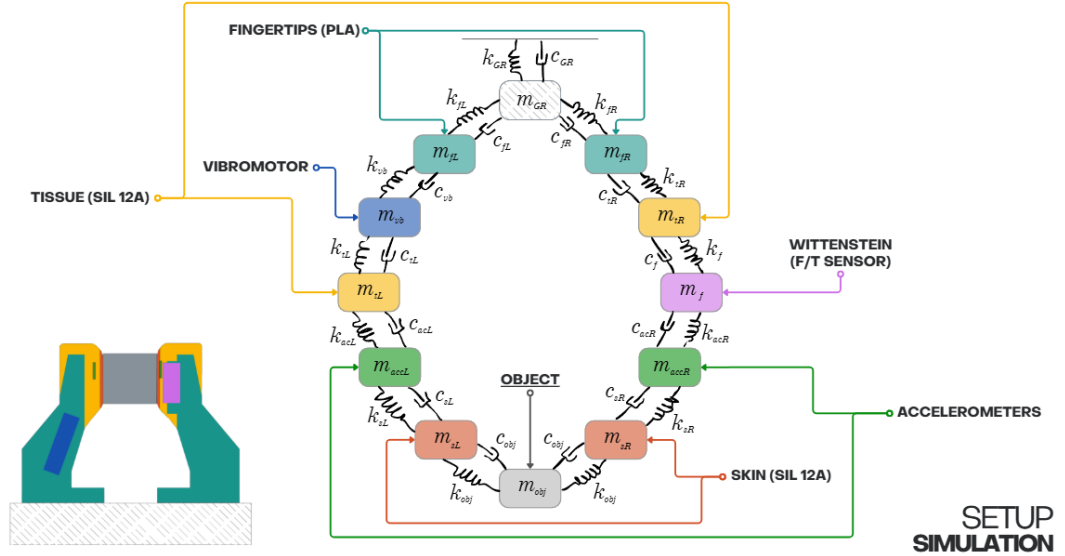


Figure 2.1: Mass Spring Dashpot System of the Gripper

In this model, the key parameters are defined that describe the mechanical meaning of the system, where;

- The lumped masses represent the effective masses of the gripper fingers,
- The springs are defined that describe the structural stiffness, along with the contact stiffness

- Damping elements are used to indicate the energy dissipation due to material damping and contact interactions.
- Mechanical connections between the fingers are represented by using the coupling elements.

The goal of the reduced-order model is not to reproduce every detail of the physical system but to capture the dominant features observed in the experimental spectra. By keeping the model simple, the physical meaning of the identified vibration modes is easier to interpret.

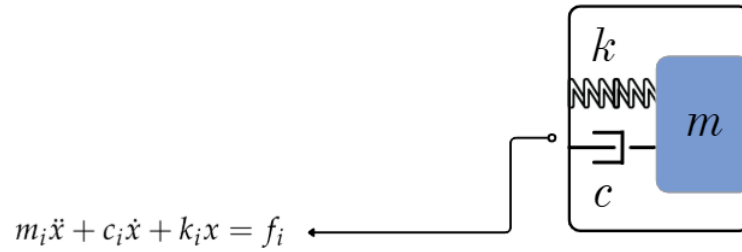


Figure 2.2: Mass spring damper with governing equation

The governing equation of the system is given by in ??:

$$M\ddot{x} + C\dot{x} + Kx = F(t) \quad (2.10)$$

To compute the eigenfrequencies and mode shapes of the system, the reduced-order model is implemented, and simulations are done using COMSOL Multiphysics software. Parameter tuning was done to get the closest modes to the experimental ones. The identified modes after parameter tuning, specifically tuning the stiffness of finger bones and tissues using eigen-frequency study, are compared to the experimentally identified modes.

The model was reduced to a simplified one because reduced-order models better interpret the physics of complex systems to determine the dominant dynamic behavior of the system [11].

2.7 Eigenvalue Problem in Structural Analysis

This study uses eigenvalue analysis for the interpretation of vibration transmissibility of the system because the spectrum of transmissibility describes resonance and anti-resonance features to describe the shape of vibrations traveling from Tx to Rx. These spectral features correspond to the natural modes of the mechanical system [7].

A transfer function can interpret the transmissibility by comparing the input and output signals in the frequency domain [11]. Therefore, identifying eigenfrequencies and eigenmodes can make it possible to know about the origin of the resonance features that are hidden in the time series of the experimental data.

2.7.1 Mathematical Representation and Interpretation

For solving dynamic response of a structure, the foundation is always the general equation of motion where the unknowns are the acceleration, velocity and displacement for all points over the structure. The dynamic behavior of a mechanical system can be described using the standard second-order equation of motion:

$$M\ddot{x}(t) + C\dot{x}(t) + Kx(t) = F(t) \quad (2.11)$$

where:

- M is the mass matrix
- C is the damping matrix
- K is the stiffness matrix
- $x(t)$ is the displacement vector
- $F(t)$ is the external excitation force

Since natural frequencies and associated mode shapes are a structure's property and are independent of any loads, the load ($F(t) = 0$) in this case will be zero.

Additionally, for general modal analysis, we do not typically need to indicate the effects of damping in the solution of the eigenvalue problem; therefore, in general, the damping factor is neglected for eigenvalue analysis. After these considerations, the equation of motion reduces to the following equation containing only the mass and stiffness matrices.

$$M\ddot{x}(t) + Kx(t) = 0 \quad (2.12)$$

This equation represents a free and undamped system, and looking at this equation, if we view it as a time-domain dynamic problem, it basically describes a structure sitting somewhere in a static position without any motion or with constant velocity, which essentially describes zero acceleration in the system.

So, in the time domain, it is not all that useful or meaningful to solve it with zero loading or zero acceleration. However, if we treat it as a frequency domain problem, we can get very interesting and meaningful results.

To solve the equation above, we assume a harmonic motion for every point of the structure, where we assume that every material of a structure is a spring-mass system and

that each of these points is vibrating at the same frequency but with different amplitudes, or magnitude of the deformation and phase angle, which we can consider as the relative timing of the vibration.

We assume a harmonic of the form

$$x(t) = \phi e^{i\omega t} \quad (2.13)$$

where ϕ is the mode shape vector and ω is the angular frequency.

Substituting this solution into the equation of motion gives the equation for the generalized eigenvalue problem:

$$(K - \omega^2 M)\phi = 0 \quad (2.14)$$

The equation of motion is now simply in terms of only angular frequency (ω) and amplitude (ϕ). This is a typical eigenvalue problem. The trivial solution to this equation would be that $\phi = 0$ which does not give a meaningful solution. The meaningful or non-trivial solution is to set the determinant of the matrix to be equal to zero. So, solving the determinant will find the square of angular frequency (ω), and it is given by:

$$\det(K - \omega^2 M) = 0 \quad (2.15)$$

Solving this equation gives the eigenvalues and eigenvectors of the system. Eigenvalues correspond to natural frequencies, and eigenvectors represent mode shapes. These modal properties define how vibration energy propagates through the system and explain observed resonance behavior [4].

2.7.2 Eigenvalues and Natural Frequencies

The eigenvalues of the eigenvalue problem represent the squared natural angular frequencies of the system, and there will be an angular frequency for every degree of freedom in the system.

$$\lambda = \omega^2 \quad (2.16)$$

The natural frequency f_n can then be computed as

$$f_n = \frac{\omega}{2\pi} \quad (2.17)$$

A mechanical structure at its natural frequency can vibrate freely without requiring an external force, and when one of the frequencies caused by the excitation equals one of the natural frequencies of the system, it leads to resonance, and consequently, the system starts vibrating at larger amplitudes. The resonance peaks in the transmissibility of the gripper are sometimes aligned with these natural frequencies, which represent the dominant features of the physical system. Therefore, identifying these frequencies is essential for explaining the system behavior.

2.7.3 Choosing Desired Number of Modes

To find the desired number of modes, we first need to know how many modes a structure will possess.

Theoretically, the number of modes that we can extract from a structure equals the number of degrees of freedom (DOF) of the model or the size of the system matrix.

$$\text{No of modes} = \text{DOFs} = \text{size of system matrix} \quad (2.18)$$

For example, a 2DOF spring-mass system equals 2 modes or 2 natural frequencies. In our case, since the model is reduced to 4DOF, we must get 4 modes or 4 natural frequencies for the proposed system model.

To choose the modes of interest, engineers need to choose the range of modes to be extracted, depending on the frequency range of excitation or load. In our case, we choose the modes around 500 Hz of the desired frequency region. In most cases like ours, higher frequencies are of less concern and hence are typically negligible; however, in general, which modes are needed depends on the structure and the loading environment.

2.7.4 Eigenvectors and Mode Shapes

The eigenvectors obtained from the eigenvalue problem represent the mode shapes of the system. A mode shape is defined as the deformation patterns at a certain natural frequency that describe the relative motion at different positions of the system at that specific natural frequency.

The modes shaped in the case of the robotic gripper system considered in this study indicate different vibration patterns of the two gripper fingers. For example, one mode of the system can follow the synchronous motion of the fingers, and another mode may be represented by opposite motion between the fingers.

How vibration energy penetrates through the fingers coupling region or the contact object from the transmitting finger to the receiving finger can be explained by these mode shapes.

2.7.5 Eigenfrequency Analysis in COMSOL

Using the reduced-order model developed in COMSOL, the eigenfrequency analysis is performed to compute the natural frequencies and the mode shaped of the model and compare then with the natural frequencies and mode shapes obtained from spectral analysis of the experimentally measured vibration response.

Parameter Tuning

With initial model parameters estimated from the experimental data resulted in eigenfrequencies which were much higher than the experimental observations. Therefore, to adjust this issue, stiffness values were chosen by reducing them 100 times than the initial defined values which can be represented by:

$$k_{\text{adjusted}} = \frac{k_{\text{initial}}}{1000} \quad (2.19)$$

By further adjusting the stiffness values of the system, the model was able to produce frequencies very close to experimentally observed modes in the frequency range of 300 to 700 Hz.

The computed eigenfrequencies are then compared with the resonance features observed in the experimental transmissibility spectrum. If the locations of these frequencies match the experimentally observed peaks, it indicates that the reduced-order model successfully captures the main dynamic behavior of the robotic gripper.

2.7.6 Analysis of Contact Effects

The contact effects of the grasp object are determined after investigating the baseline behavior in the void case. The interaction between the gripper and the contact object changes the modal properties and the transmissibility behavior by modifying the parameters of the system such as stiffness and damping [2]. This behavior is represented by using additional stiffness and damping elements between the gripper fingers and the contact object. The natural or resonance frequencies of the system shift with changes in contact parameters such as increasing the stiffness of the contact, and it also alters the vibration transmission characteristics by showing changes in vibration amplitudes [7].

By comparing the transmissibility spectra of the void case and the contact case, we can analyze the influences of contact interactions on the system dynamics.

Chapter 3

Results and Discussions

3.1 Analysis of Measured Signals (Void Case)

3.1.1 Initial Spectral Estimation (Raw)

The initial analysis of the experimental time-series data was performed using auto-spectral density and cross-spectral density analysis for the transmission and reception signals using the Welch method.

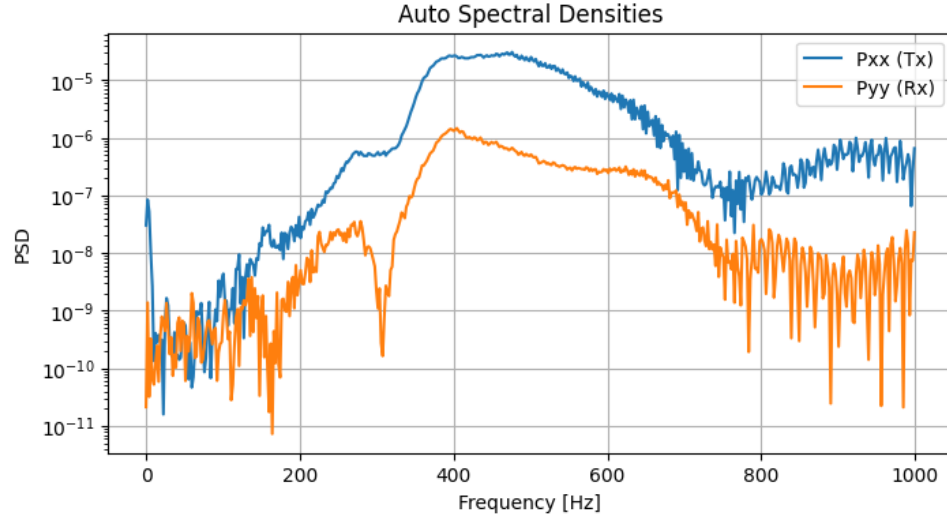


Figure 3.1: Raw Auto-Spectral Densities (Tx and Rx)

The preliminary view of the distribution of vibrational energy can be seen by in both signal in Fig. 3.1, where, the Tx signal shows an increased energy in the mid-frequency range, and the Rx follows along but with lower magnitude, which indicates attenuation during transmission process. Even though both spectra show some peaks, the exact peaks are unclear due to significant fluctuations.

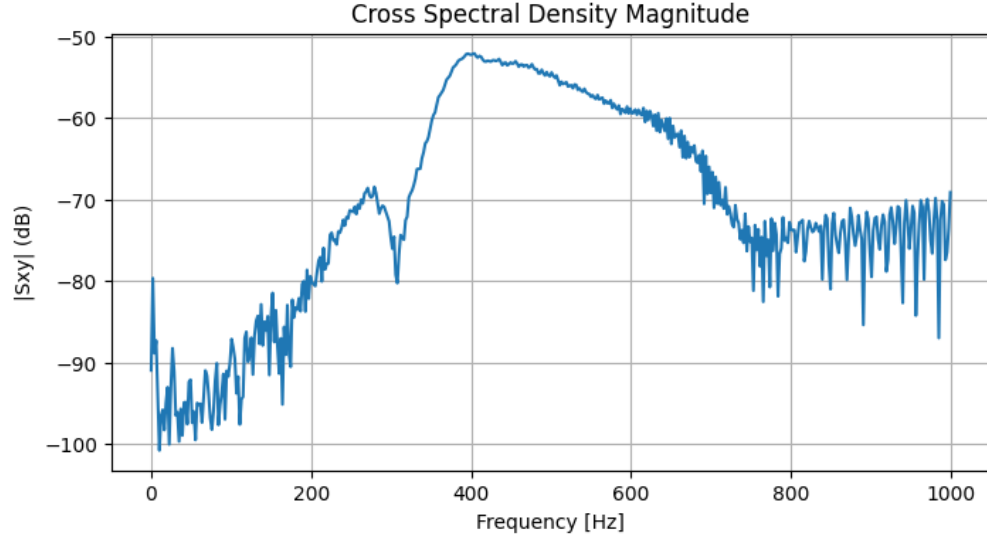


Figure 3.2: Raw Cross-Spectral Density

The Fig. 3.2, represents the cross-spectral density which depicts a picture of the coupling between the Tx and Rx signals. The middle part of the plot shows the level of correlation between the signals as indicated by an increase in magnitude in that region.

However, cross-spectrum still is not smooth just like the auto-spectral densities. Because of this, identifying clear frequency components and coupling behavior of the response requires further signal processing techniques such as filtering for reliable interpretation.

Inferring real system behavior from raw data becomes difficult due to a large segment length use for averaging which result in reduction in the number of segments used for averaging process.

Overall, the irregular nature of the raw data shows the insufficient averaging in the spectral estimation process. Due to this, identifying meaningful dynamic modes and features from the raw spectral estimates is inadequate.

3.1.2 Improved Spectral Analysis

Auto spectral densities are refined by increasing the number of averaged segments by reducing the length of segment which made smoother response compared to raw results as shown in Fig. 3.3.

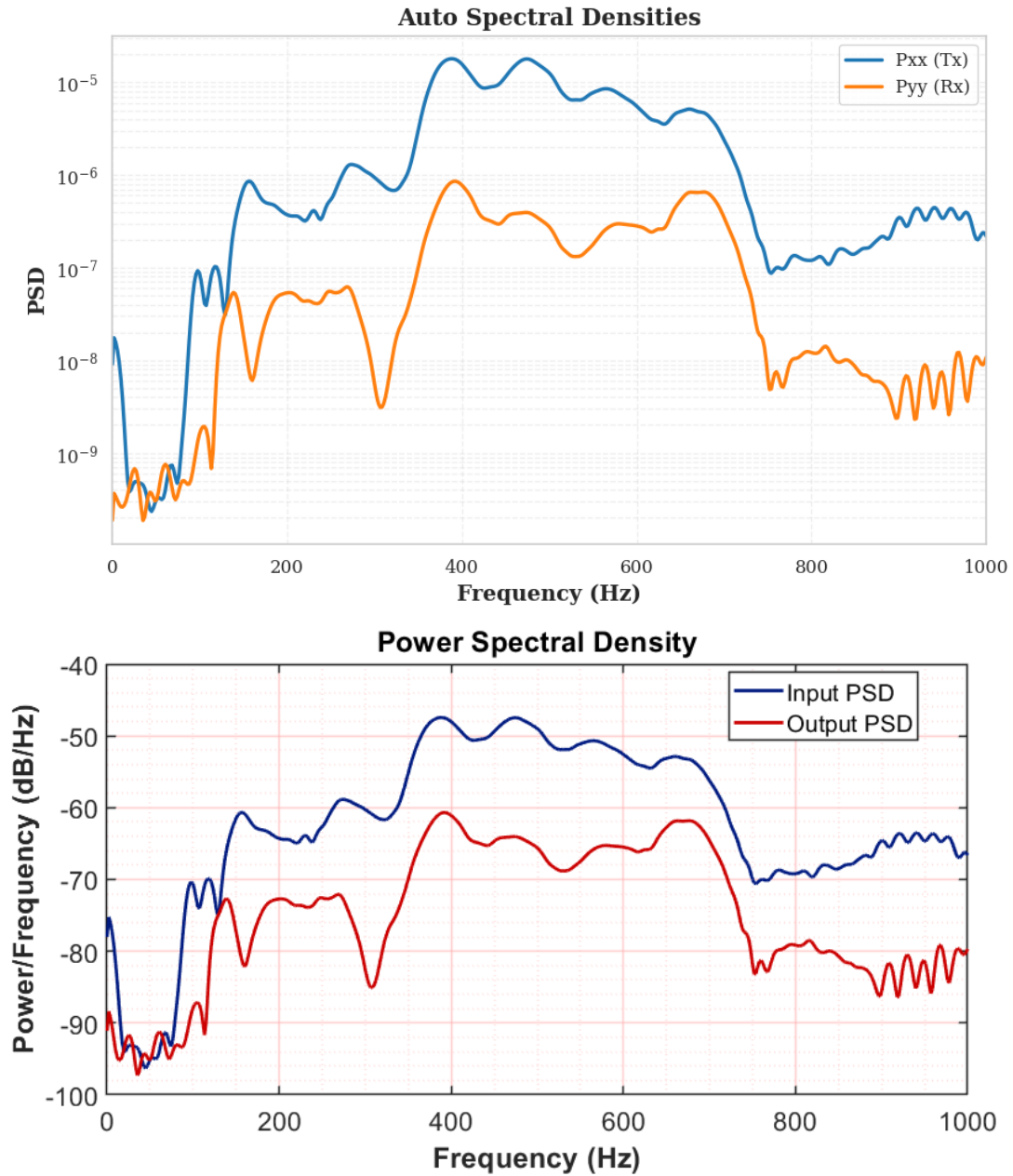


Figure 3.3: Improved Auto-Spectral Densities (Python/MATLAB)

The Tx spectrum and Rx spectrum now clearly shows multiple peaks in the frequency range of 350 Hz – 650 Hz. The refined spectrum of the Rx signal also shows a distinct dip around 250 – 300 Hz which indicates suppression in vibration transmission representing an anti-resonance effect.

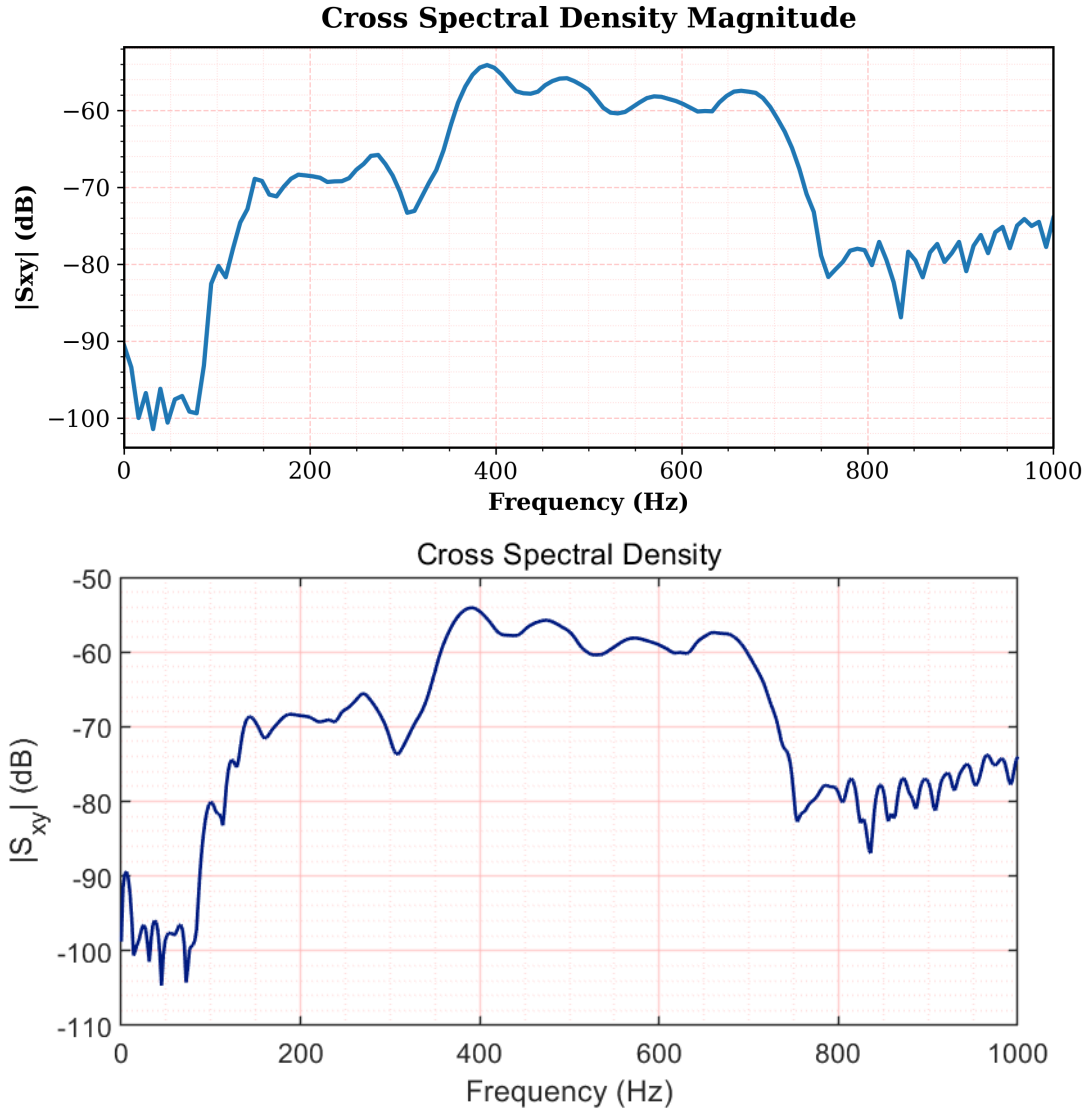


Figure 3.4: Refined Cross-Spectral Density

The refined cross-spectral density, shown in Fig. ??, indicates a strong coupling region around 350 Hz – 650 Hz, represented by the highest cross-spectral magnitude.

The exterior regions at low and high frequencies corresponding to (<200 Hz) on the left and (>700 Hz) on the right where the cross-spectrum is decreasing mean that the signal in these regions is either noise or less reliable.

3.1.3 Frequency Response Function Analysis

The response of the system to any excitation in specific frequency is understood by the application of the frequency response function (FRF). The FRF magnitude plots computed using the Python (left) and MATLAB (right) are shown in Fig. 3.5 and both show

consistent behavior.

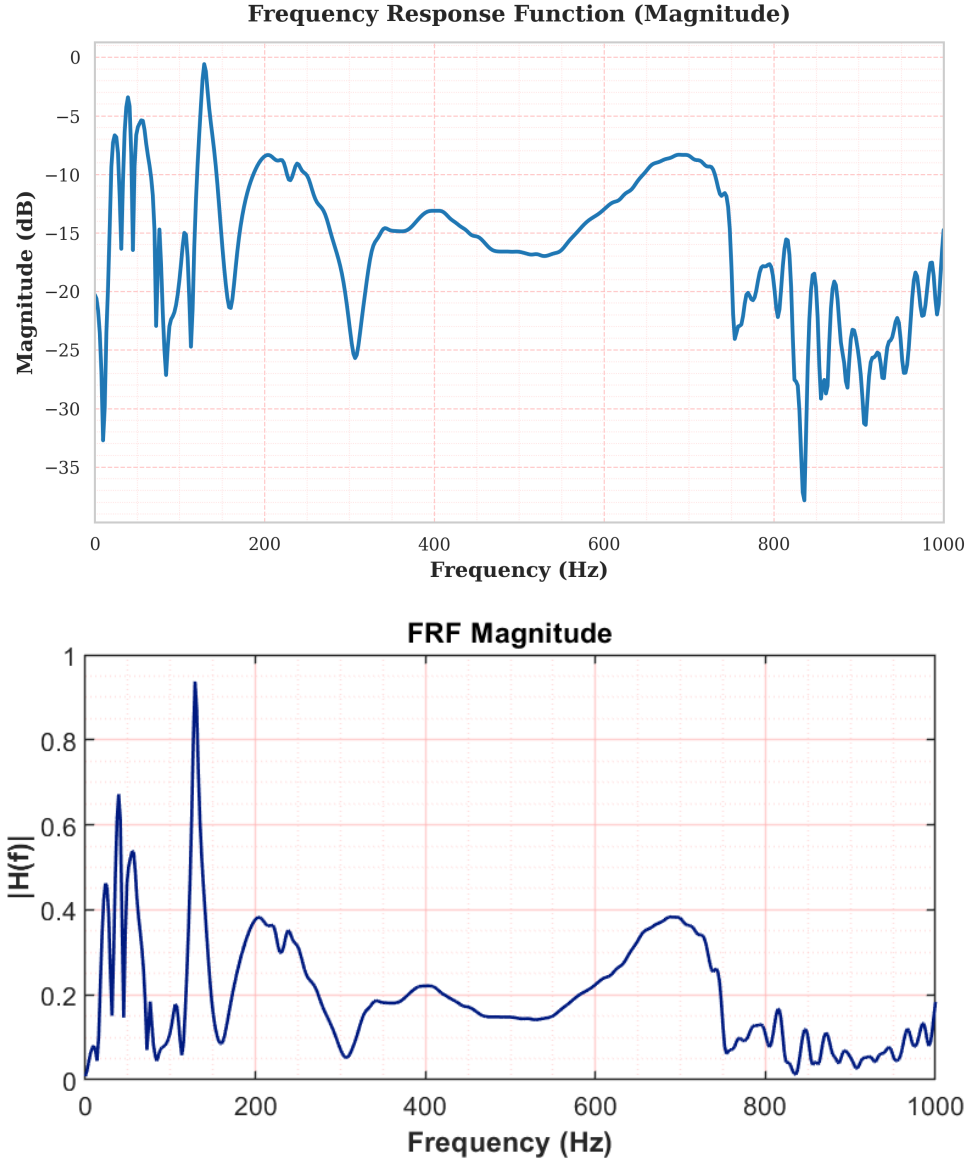


Figure 3.5: Frequency Response Function Magnitude (Top: Python, Bottom: MATLAB)

From both plots, it is clear to see multiple peaks within the frequency range of approximately 350 Hz to 650 Hz. This indicates that within this range the potential resonant frequencies are present. The similar peaks in both plots means the dynamic characteristics of the system are consistent and coherent. The weaker and less structured response that seems outside of this range means the system participation is less in these regions.

The observed resonant behavior can further be seen from the FRF phase plots from Python (left) and MATLAB (right), in Fig. 3.6 and the phase transition is also observed around frequencies corresponding to the magnitude peaks.

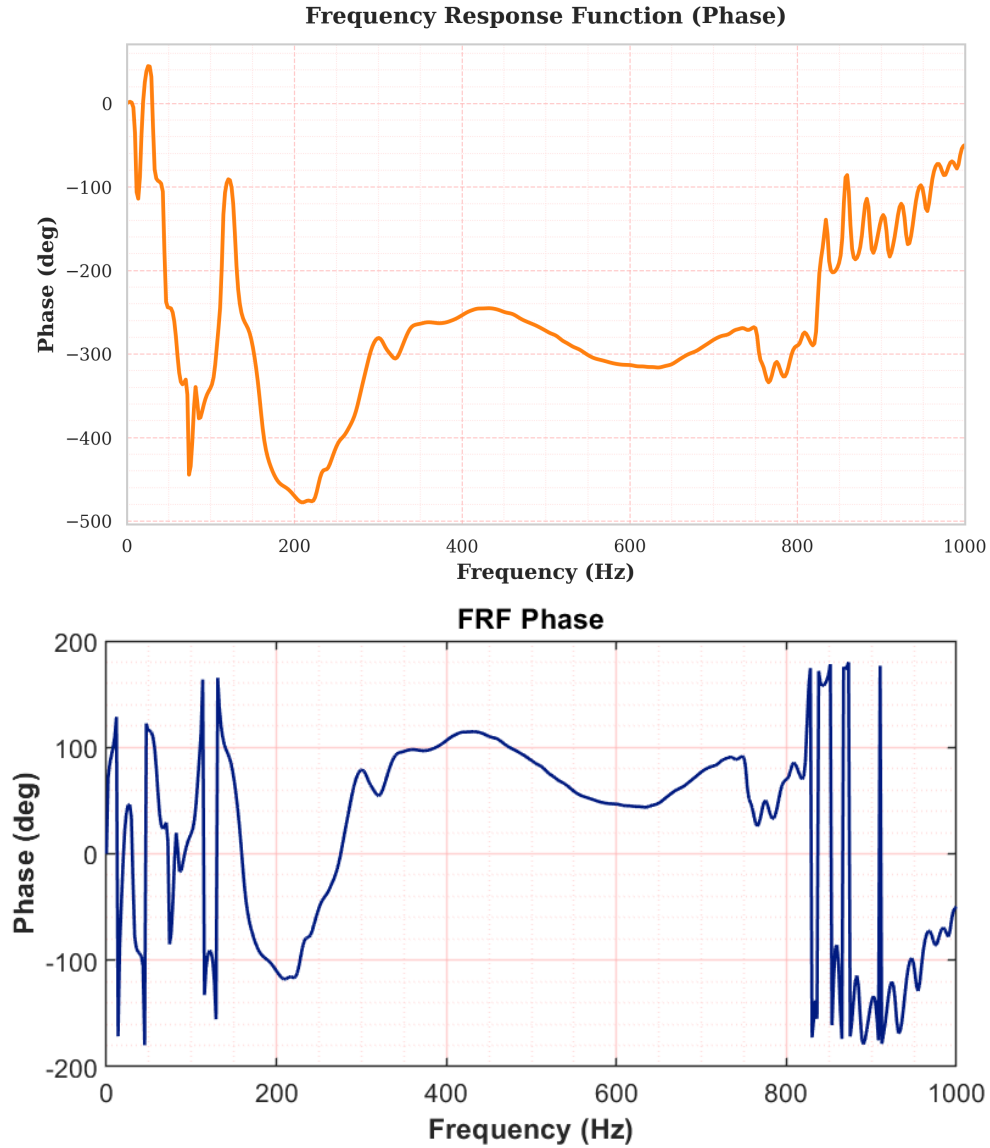


Figure 3.6: Frequency Response Function Phase (Top: Python, Bottom: MATLAB)

3.1.4 Magnitude-squared coherence

While the refined spectral estimates provide a clearer representation of the system dynamics, it is still necessary to assess the reliability of these observations. To further zoom into the refined spectra for more reliable observations, the magnitude-squared coherence has been calculated using the auto-spectral and cross-spectral densities.

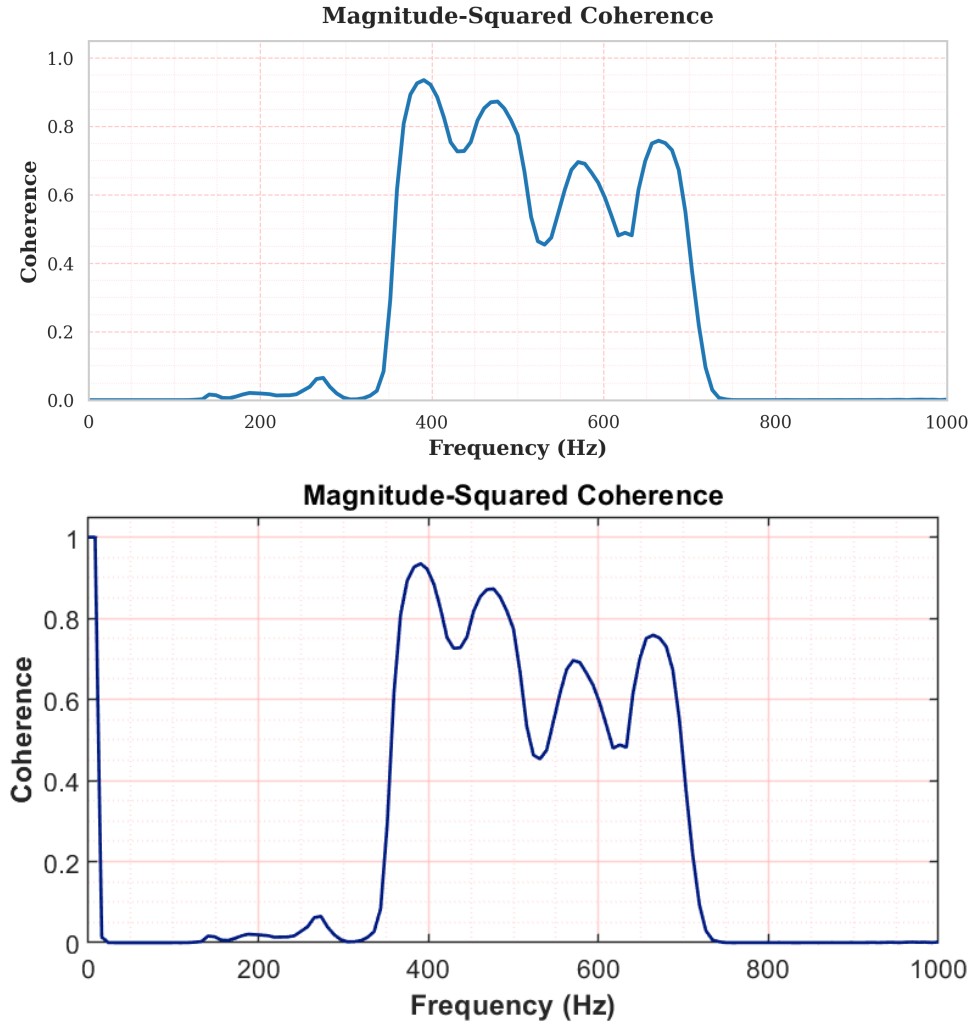


Figure 3.7: Magnitude-Squared Coherence (Top: Python, Bottom: MATLAB)

A well-defined frequency band is observed in Fig. 3.7, by the coherence function with high coherence values between 350 Hz and 720 Hz which indicated strong relationship between the transmitting and receiving signals in this region. This confirms physically meaningful features in this region.

These observations show the importance of coherence in spectral analysis that can help us to separate noise from real dynamic behavior of a mechanical system. This can identify the frequency regions which are suitable for modal analysis.

3.1.5 Identification of Reliable Frequency Bands

From the magnitude-squared coherence, the frequency regions showing the reliable relationship between the transmitter and receiver were identified. By defining a coherence threshold of 0.6 (in Fig.3.6), the useful frequency regions were separated from noise-

dominated frequencies. Only frequencies with coherence values exceeding this threshold were considered physically meaningful, while the rest were discarded from subsequent analysis.

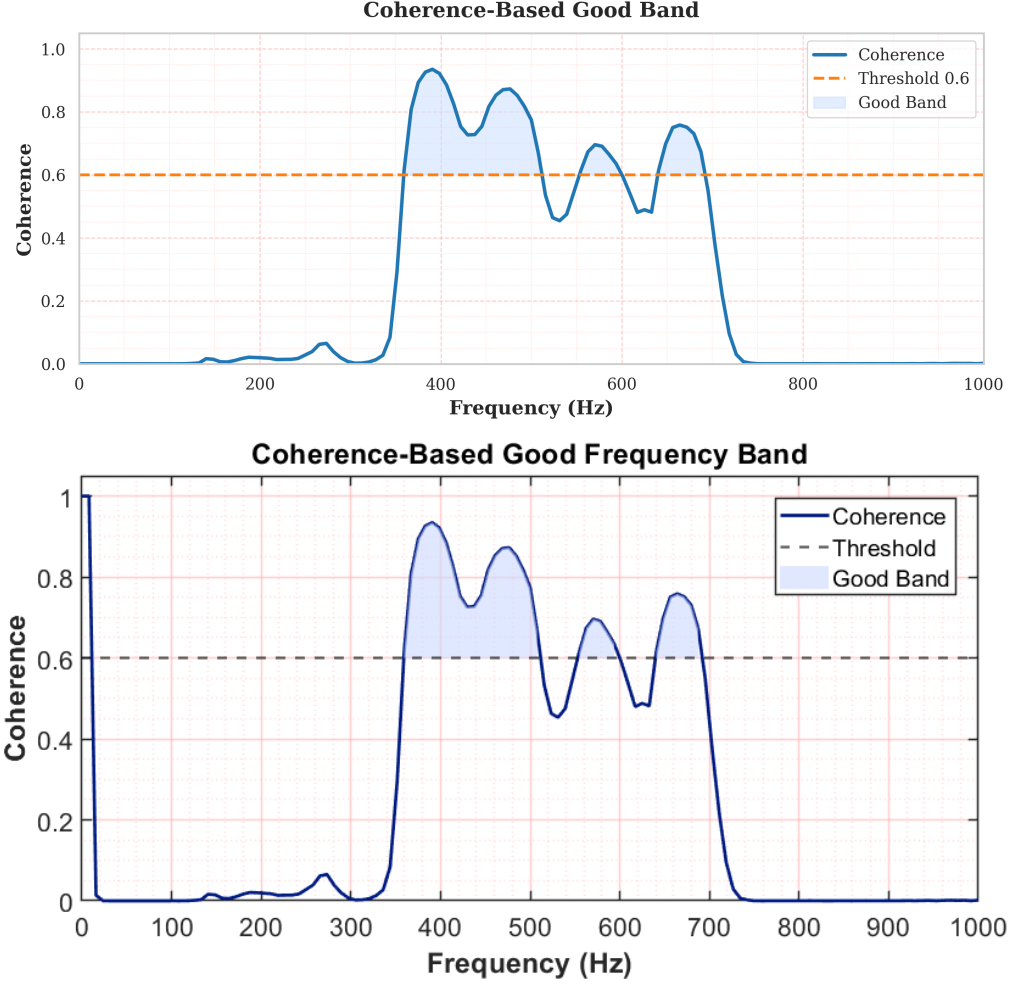


Figure 3.8: Magnitude-Squared Coherence (Top: Python, bottom: MATLAB)

By the application of this threshold, three distinct high-coherence frequency bands were seen in the system which are given below:

- 359.4 Hz – 515.6 Hz
- 554.7 Hz – 601.6 Hz
- 640.6 Hz – 695.3 Hz

Importantly, we can see from the coherence-based filtering, the coherence is separated by reduced coherence regions which show its segmentation represented by multiple intervals. This means all the frequencies from 350 - 700 Hz are not equally important.

3.1.6 Extraction of Valid Modal Frequencies

From the coherence-based bands, we observe the regions where signal interaction is reliable. The next step to find dominant modes along with corresponding frequencies in these regions. This was achieved by detecting peaks in the frequency response function which indicate strong coupling between Tx and Tx using the cross-spectral density analysis but, in fact, all the detected peaks cannot describe physically meaningful modes. Therefore, to detect meaningful modes from the high-coherence regions, a filtering was applied.

The valid modal frequencies are identified from the filtering step as:

- 128.906 Hz
- 203.125 Hz
- 404.296 Hz
- 687.50 Hz

The last two modes appear in the coherence band represent the physical behavior of the system and the first two modes are ignored due to they being appear outside the coherence band which makes them useless.

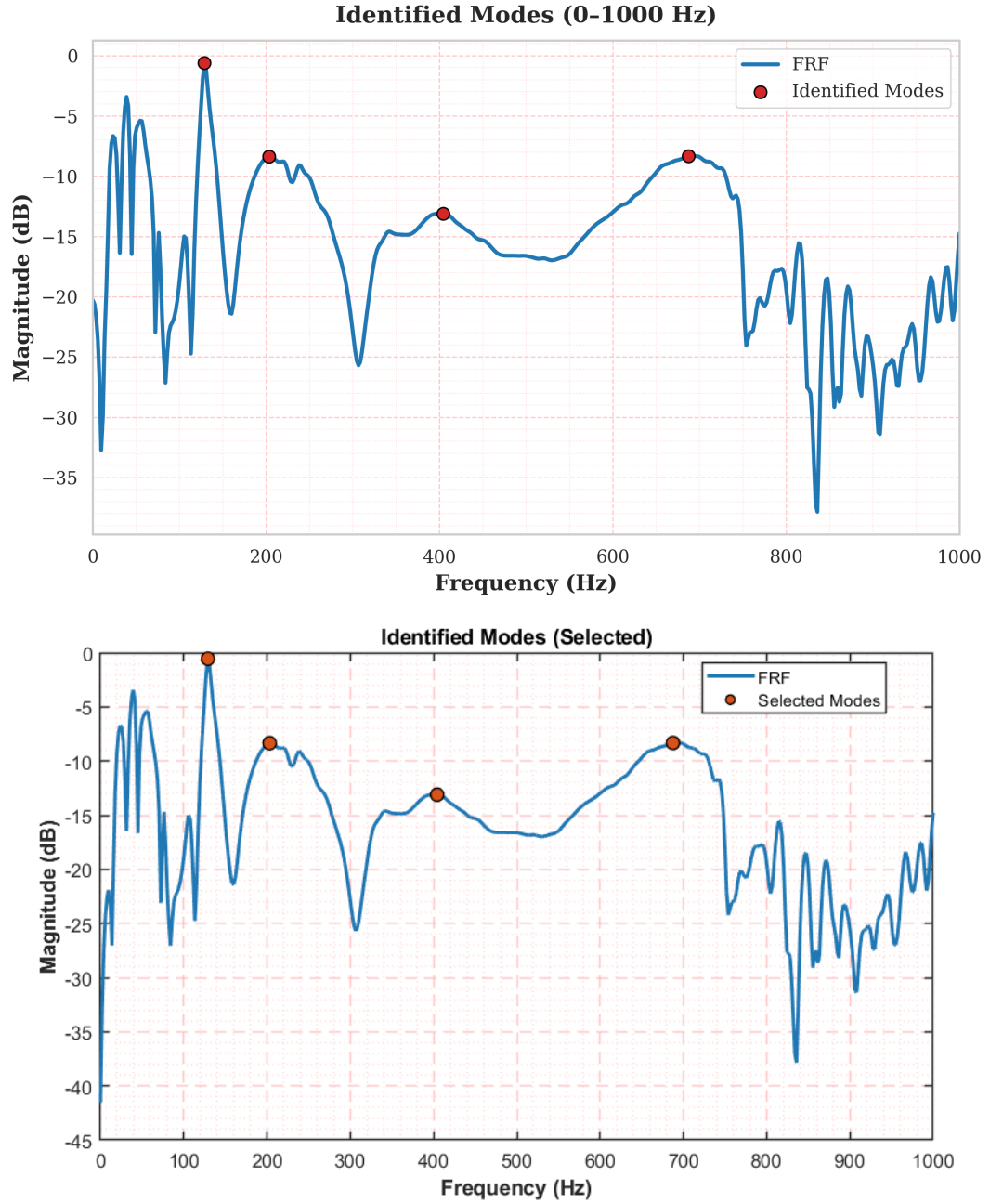


Figure 3.9: Identified Modes from FRF (Left: Python, Right: MATLAB)

Since the system modes are distributed across multiple coherence bands, it means the system is represented by multiple resonant behavior. The separation between the bands shows reduced transmission efficiency at certain frequency regions.

These experimentally identified modes form the basis for comparison with the reduced-order model and COMSOL simulations, where the goal is to determine whether the same dominant dynamic features can be reproduced by a simple model.

3.2 COMSOL Results

To obtain natural frequencies through the reduced-order model, and compare them with the experimentally identified modes, an eigenfrequency study was used and the stiffness values of finger bones and tissues for both Tx and Rx was adjusted.

Along with stiffness adjustments, this analysis is done by choosing the aroudshift frequency around 500 Hz to find the meaningful frequencies in 300-700 Hz range.

From this analysis, COMSOL determines the eigenfrequencies and corresponding modes of the proposed system by solving the generalized eigenvalue problem derived from the discretized mechanical system.

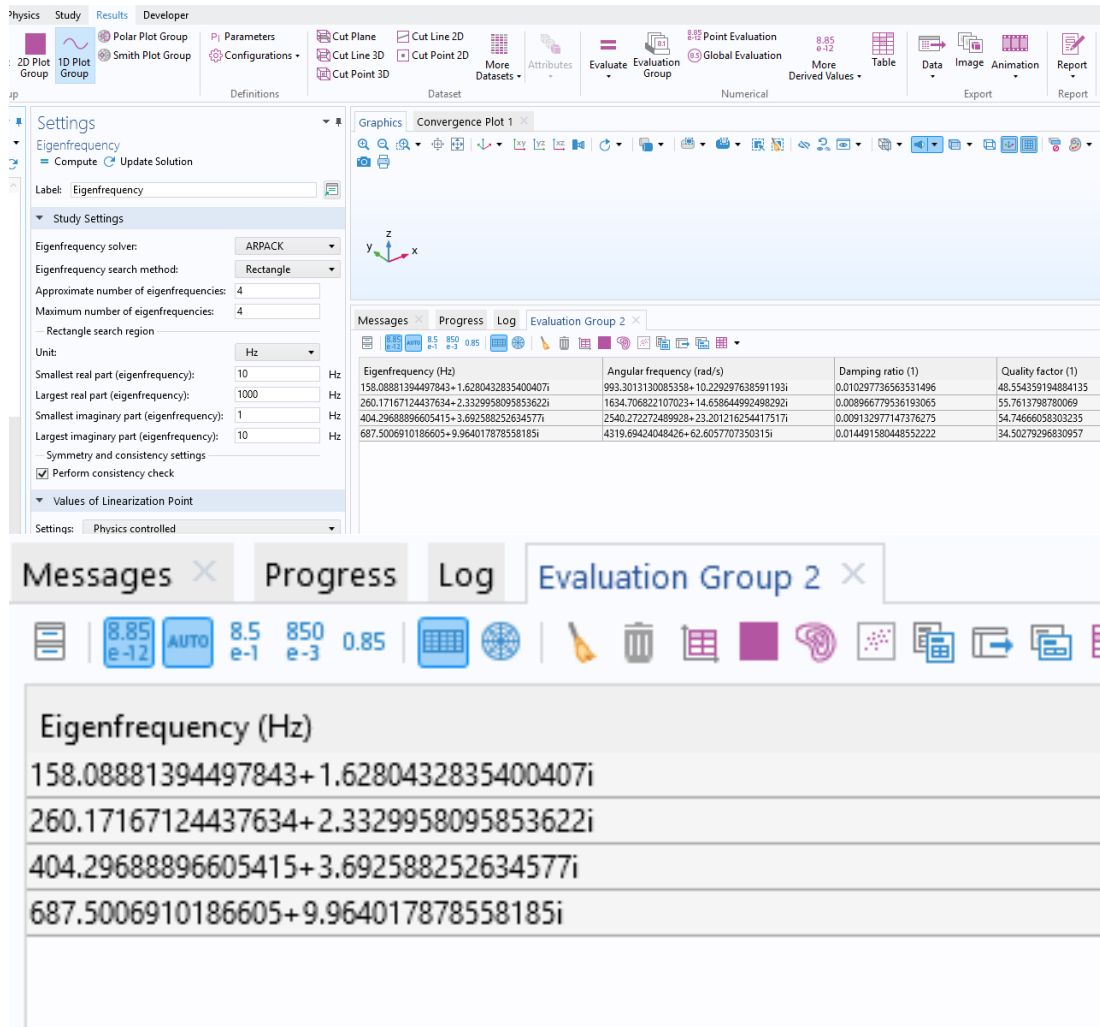


Figure 3.10: Eigenfrequencies using Reduced-Order Model

The natural frequencies obtained using the analysis of eigenfrequency of the model are:

- 158.088 Hz
- 260.171 Hz
- 404.296 Hz
- 687.500 Hz

3.2.1 Comparison of Experimental and Numerical Modes

From the comparison, it is observed that COMSOL showed two similar modes as experimental which are:

- The eigenfrequency at 404.296 Hz in COMSOL is same as the experimental mode at the exact frequency 404.296 Hz computed using Python and MATLAB.
- Another desired mode was observed at 687.500 Hz in experimental analysis is in parallel to the COMSOL at the same frequency.

This shows that the dynamic behavior of the system at desired higher frequency is successfully captured by the reduced-order model. However, the model showed discrepancies for the lower frequency range; the two modes appear at the lower frequencies are of no interest because they do not come under the desired coherence band so we ignore the undesired frequencies appear in the system.

3.2.2 FRF Comparison Between Experimental and COMSOL Results

To validate the experimentally identified modes, the frequency response obtained from the numerical model is compared with the experimentally derived FRF from MATLAB. The comparison is shown in Fig. 3.11.

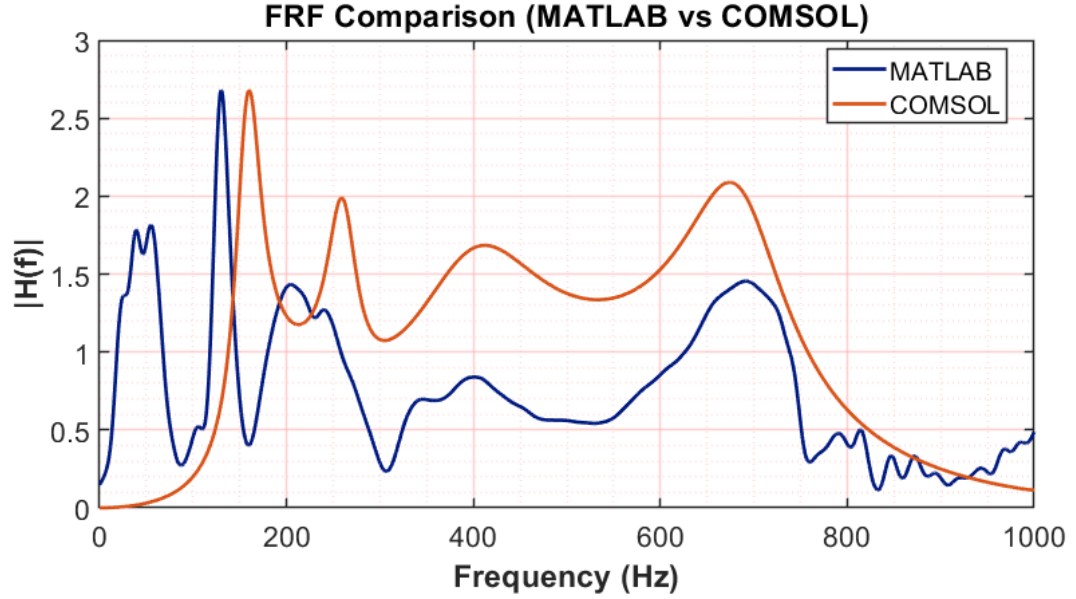


Figure 3.11: FRF Comparison (MATLAB vs COMSOL)

The comparison between the FRF from modal analysis and the FRF computed in COMSOL determines that the COMSOL follows the experimentally computed FRF in the desired frequency range and the dominant peaks in both responses are same in particular.

Since we were interested in the coherence frequency range and we can clearly see the two modes of interest are closely matched in both results. It means these are the meaningful modes that defines the actual dynamic behavior of the system.

In contrast, discrepancies observed at lower frequencies are outside the coherence band and are therefore not considered reliable for modal interpretation.

The close alignment between the experimental and numerical FRFs demonstrates that the model accurately gives the key dynamic characteristics of the system. Consequently, the matched peaks are identified as the natural frequencies of the system.

3.3 Conclusion

The comparison between the experimental and COMSOL analysis outcome suggests that the model was able to represent the dynamic behavior of the system. It was enabled to copy the exact behavior of the system in the desired frequency range. These matches between the experimental and COMSOL results show the performance of the reduced order model. The common higher frequency modes are significant as they exist in the higher-coherence band observed experimentally. Therefore, the identified common modes indicate that these modes are physically meaningful as they have been validated through experimental analysis as well as by using the model. This means the reduced-order model can represent the physical meaning of the system dynamics, specifically in the vibration transmission frequency range.

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