A Framework for Prediction in a Fog-Based Tactile Internet Architecture for Remote Phobia Treatment

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ABSTRACT

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Tactile Internet, as the next generation of the Internet, aims to transmit the modality of touch in addition to conventional audiovisual signals, thus transforming today's content-delivery into skill-set delivery networks, which promises ultra-low latency and ultra reliability. Besides voice and data communication driving the design of the current Internet, Tactile Internet enables haptic communications by incorporating 5G networks and edge computing. A novel use-case of immersive, low-latency Tactile Internet applications is haptic-enabled Virtual Reality (VR), where an extremely low latency of less than 50 ms is required, which gives way to the so-called Remote Phobia treatment via VR. It is a greenfield in the telehealth domain with the goal of replicating normal therapy sessions with distant therapists and patients, thereby standing as a cost-efficient and time-saving solution.

In this thesis, we consider a recently proposed fog-based haptic-enabled VR system for remote treatment of animal phobia consisting of three main components: (1) therapist-side fog domain, (2) core network, and (3) patient-side fog domain. The patient and therapist domains are located in different fog domains, where their communication takes place through the core network. The therapist tries to cure the phobic patient remotely via a shared haptic virtual reality environment. However, certain haptic sensation messages associated with hand movements might not be reached in time, even in the most reliable networks. In this thesis, a prediction model is proposed to address

the problem of excessive packet latency as well as packet loss, which may result in quality-of-experience (QoE) degradation. We aim to use machine learning to decouple the impact of excessive latency and extreme packet loss from the user experience perspective. For which, we propose a predictive framework called Edge Tactile Learner (ETL). Our proposed fog-based framework is responsible for predicting the zones touched by the therapist's hand, then delivering it immediately to the patient-side fog domain if needed. The proposed ETL builds a model based on Weighted K-Nearest Neighbors (WKNN) to predict the zones touched by the therapist in a VR phobia treatment system. The simulation results indicate that our proposed predictive framework is instrumental in providing accurate and real-time haptic predictions to the patient-side fog domain. This increases patient's immersion and synchronization between multiple senses such as audio, visual and haptic sensory, which leads to higher user Quality of Experience (QoE).

Dedicated to

My Parents

And

My Love

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List of Acronyms and Abbreviations

5G	The Fifth Generation of the Mobile Communication system
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Augmented Reality
CBT	Cognitive Behavioral Therapy
eMBB	enhanced Mobile Broadband
HTTP	Hypertext Transfer Protocol
HITL	Human-In-The-Loop
IaaS	Infrastructure-as-a-Service
IoT	Internet of Things
***K*NN**	K-Nearest Neighbors
MEC	Multi-access Edge Computing
MTC	Machine Type Communications
M2M	Machine-to-Machine
ML	Machine Learning
NB	Naïve Bayes
PaaS	Platform as a Service

QoE	Quality of Experience
QoS	Quality of Service
REST	Representational State Transfer
RFID	Radio Frequency Identification
SaaS	Software-as-a-Service
URLLC	Ultra-Reliable Low-Latency Communications
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VMs	Virtual Machines
VRE	Virtual Reality Environment
VR	Virtual Reality
WKNN	Weighted K-Nearest Neighbors
WLAN	Wireless Local Area Network
WG	Working Group

Chapter 1

Introduction

This thesis begins with an introduction of the key concepts that shape the foundation of our research. The motivation and the goal of this work are also elaborated in the next sections.

1.1 Definition

This section is dedicated to the definitions of the key terms associated with the thesis. The definition includes Tactile Internet, Remote Phobia Treatment via Virtual Reality, Cloud and Edge Computing, and Machine Learning.

1.1.1 Tactile Internet

Tactile Internet brings a new paradigm shift from content-based to skill-based delivery over the Internet. Tactile Internet is expected to enable real-time delivery of haptic sensations as well as conventional visual and auditory data over the Internet [1]. The haptic sensation word in Tactile Internet refers to tactile sensation (feedback) and kinesthetic sensation. Tactile sensation comprises the sense of texture and temperature of an object, especially on the surface of human skin. Tactile sensation can be experienced from vibration, heat, and pressure [1]. In contrast, the kinesthetic feeling enables the user to realize the size and weight of an object [2]. Haptic devices are categorized into three main groups, namely: graspable, wearable, and touchable devices using the kinesthetic sensation of Tactile Internet.

Tactile Internet can be considered as an evolutionary phase of the Internet of Things (IoT) [2]. It is expected to be enabled by fifth-generation of mobile telecommunication technology (5G) [3]. IoT is defined as a set of sensors, actuators, mobile phones, and RFID tags which are interacting and communicating with each other to reach a common goal [4].

There are three essential requirements to realize the Tactile Internet. The first requirement is ultra-low latency, which means providing the ultra-responsiveness in the order of 1 to 100 ms, depending on the use case, to respect the time-sensitivity of the Tactile Internet applications [5]. The second requirement is ultra-high reliability of 99.999% [5]. The ultra-reliability requirement also differs from one use case to another according to types of services. The third key requirement of Tactile Internet is security and privacy.

1.1.2 Remote Phobia Treatment via Virtual Reality

The excessive fear of something is considered a phobia. There are two main types of psychological treatment for anxiety disorders in general, including anxieties caused by phobia: Exposure Therapy and Cognitive Behavioral Therapy (CBT). During exposure therapy, the therapist tries to expose the patient gradually with the feared object. However, in CBT, in addition to exposure therapy, the therapist attempts to change the patient's way of thinking and use various techniques for identifying the feared situation or object [6].

In recent years, with advent of technology, scientists try to create a Virtual Reality Environment (VRE) for building a way to expose patients with their phobia gradually instead of direct exposure to small animals or their fears [7]. The degree of exposure within treatment sessions is controlled by the therapist [6]. Virtual Reality Phobia therapy provides a safe and controlled human-computer interaction [8]. The virtual reality environment aids individuals who suffer from anxiety disorders due to fear of specific objects (e.g., spider), flying, heights, elevators, and public speaking. Reasonable responses have been reported from such a virtual reality treatment mechanism [9]. Remote phobia treatment via Virtual Reality is one of the most attractive use cases of Tactile Internet and 5G networks. It aims at replicating regular therapy sessions with distant therapists and patients. Equipment such as VR headsets and wearable haptic devices (e.g., gloves) in VR, make the experience of virtual reality more immersive. Incorporation of VR with auditory, visual, and haptic feedback provides a more tangible perception of virtual reality for both patient and therapist.

1.1.3 Cloud and Edge Computing

Cloud Computing is a paradigm that refers to the provisioning of a shared pool of virtualized resources. Also, it allows pay-per-use and on-demand provisioning of resources such as storage, application, services, and network. Cloud computing has three main facets: Infrastructure-as-a-Service (IaaS), Platform as a Service (PaaS), and Software-as-a-Service (SaaS) [10]. Although cloud computing offers elasticity and scalability, it still encounters latency problems due to the distance between the cloud and end-user [10].

Edge Computing is known as “edge”, which brings the processing close to the devices where it is not required to have the data sent to the cloud. Therefore, the performance can be improved by eliminating the distance and time it takes to send data to the cloud [10]. Edge computing, including fog computing, also emerges as a complement for cloud computing, which helps minimize network latency by provisioning resources and services closer to the end device and will help toward achieving ultra-responsiveness in Tactile Internet-related applications**.** The term Fog Computing was introduced first by Cisco in 2014. “Fog Computing is a standard that defines how edge computing should work, and it facilitates the operation of computing, storage, and networking services between end devices and cloud computing data centers" [11]. It is a way to extend computing to the edge of the network. In essence, fog is the standard, and edge is the concept.

1.1.4 Machine Learning

Machine Learning (ML) is a scientific approach which enables the deployment of intelligence based on different learning mechanisms through various algorithms [12]. Machine learning task accomplishments are classified into supervised, unsupervised, and reinforcement learning categories.

Supervised learning automatically addresses an input signal to output since the supervised learning model includes the desired output. The goal of supervised model learning is to predict discrete or continuous values based on labeled data. A labeled or tagged dataset enables supervised learning algorithms to train the model based on the observed historical data which is well organized. However, in unsupervised learning, the descriptive model has been built based on unlabeled data. There are no specific categories or labels which can aid mapping between input and output data [12]. Third, reinforcement learning methods aim at utilizing gathered observations from the environment to maximize reward and minimize risk [13].

1.2 Motivation

According to an epidemiological study in [14], approximately 6.2%-8.0% of the Canadian population suffers from the so-called *specific phobia,* and 4.7% is affected by small animal phobia [15]. Moreover, 12.5% of the world population suffers from a small animal phobia [16], which falls within the category of specific phobia. It is also reported that almost 9 billion dollars is spent annually on the treatment of specific phobias in the US [17]. In particular, spider ranks first among small animals causing phobia based on a recent survey conducted among 77 phobic adolescents [18]. With the recent technological advancements in virtual reality (VR) technology, a new type of phobia treatment method is emerging, where the therapist helps a patient overcome her fear by gradually exposing the patient to the phobic object in a virtual environment. Typically, the amount of exposure during the therapy session is controlled by the therapist [19].

Recently, there is a growing interest in exploiting VR for phobia treatment. Reference [21] was the first case study measuring the effectiveness of VR-based phobia treatment. The outcomes were assessed based on the patient's level of avoidance and anxiety while confronting a real spider. The results were reported satisfactory as her level of anxiety and avoidance from a real spider decreased significantly. With the introduction of advanced VR headsets and wearables such as haptic-enabled gloves, end-users are provided with multisensory information, including the haptic feedback in addition to the conventional audiovisual feedback [22]. This, in turn, allows for an immersive VR experience to provide a more tangible and realistic perception of the VR environment, which ultimately can lead to increased presence, immersion, togetherness and trust in VR. The integration of the haptic sensation within virtual space is a new paradigm, which allows both patient and therapist to touch a virtual object and feel its texture [23]. Having a real-time sensation during a treatment, though, is crucial as it allows the user to have a more realistic experience by providing her with an immersive virtual presence. The term *haptic* refers to either tactile or kinesthetic sensations. VR-based remote phobia treatment is one of the novel use cases of the Tactile Internet, and a greenfield in the telehealth domain. It aims to replicate regular therapy sessions with distant therapists and patients, thus emerging as a cost-efficient and time-saving approach. Moreover, removing the geographical constraints, allows patients to choose among a wider group of available experts. Besides, remote therapy could allow the therapist to run multiple therapy sessions at a time

Recently, a fog-enabled remote phobia treatment system has been proposed and experimentally validated in [23], which consists of three main components: (1) therapist-side fog domain, (2) core network, and (3) patient-side fog domain. The patient and therapist domains are located in different fog domains, where their communication takes place through the core network. The therapist interacts with the phobic patient remotely via a shared haptic virtual reality environment. Both the therapist and the patient are provided with the haptic feedback associated with the touched zone in the virtual space. We note, however, that during a remote phobia treatment, hand position signals, zones touched by therapist’s hand, may not reach in time from the therapist to the patient-side fog domain even in most reliable network conditions. Given that the communication between the therapist and its feedback generator takes place locally, the therapist will experience a negligible delay, as opposed to the patient, who is yet to receive the hand position haptic signals from the therapist-side fog domain. Therefore, end-to-end latency is inevitable at the patient’s side, thus making her susceptible to Quality-of-Experience (QoE) degradation due to not receiving the haptic feedback on time.

We note that excessive end-to-end latency may create an uneven time lags between different modalities (e.g., audio, video, and haptic), thus resulting in the so-called mis-synchronization [23]. The aforementioned issue, in turn, may cause cyber-sickness at the patient’s side, which may lead to Quality-of-Experience (QoE) degradation. According to [24], the end-to-end delay in a haptic-enabled VR system should not exceed 50 ms. To address the QoE degradation, in this thesis, we propose our machine learning-based prediction system, which aims at providing haptic predictions of the therapist's hand movement during a therapy session. Machine learning enables the machine to gain new skills and knowledge without being programmed. To this end, considering the criticalness of medical treatment procedures, accuracy plays a vital role, especially when there is a delay. Machine learning enables prediction of delayed messages with high accuracy and within an acceptable latency requirement of a Tactile Internet system, especially due to the capability of its models to adapt themselves with the historical data and past observations.

1.3 Goal of the Thesis

In this work, we intend to find a solution to cope with latency and data loss problems in a haptic-based remote phobia treatment system with the ultimate goal of increasing the quality of the patient's experience. We propose a solution which compensates for delayed or lost haptic messages, by predicting the zones touched by the therapist in a given 3D virtual environment. In particular, the existence of correlation patterns within the therapist's hand motion during phobia therapy may offer the possibility to predict the next zone area touched by therapist, thus enhancing the performance of haptic communication between therapist and patient.

In this thesis, we build on [23] and propose our predictive framework by the means of machine learning, which provides predictions of the zones interacted with by the therapist during a therapy session, when needed. To do so, we propose our *Edge Tactile Learner* (ETL), which builds a model based on Weighted K-Nearest Neighbors (WKNN) to run accurate predictions of the therapist's touched zones in a VR remote phobia treatment system in the VR coordinate system. The use of machine learning can effectively enhance the user (patient and therapist) experience toward the system.

1.4 Thesis Contribution

The main contributions of the thesis are as follows:

- Proposing prediction methods for a fog-based remote phobia treatment architecture introduced in the literature.
- Evaluating the effectiveness of the proposed methods in terms of accuracy.
- Assessing the proposed models based on the delay requirements of the Tactile Internet.

1.5 Thesis Organization

The present dissertation is organized into six chapters. In Chapter 2, the background knowledge related to Tactile-based remote phobia treatment, cloud and fog computing, fog-based architecture for remote phobia treatment and prediction frameworks are discussed. In Chapter 3, the system model for fog-based remote phobia treatment followed by the motivating scenario and problem statement and the set of requirements as well as related work are discussed. In Chapter 4, the proposed predictive framework called Edge Tactile Learner followed by three weighting methods are discussed. Our evaluation results and assessment of the proposed methods presented in Chapter 5. Finally, in Chapter 6 the contributions and future works that can be built based on this work are discussed.

Chapter 2

Background Information

This chapter starts by presenting the background information related to Tactile-based remote phobia treatment relevant domains followed by the cloud and fog computing paradigm. Afterwards, a fog-based architecture, along with presenting the functional entities for remote phobia treatment. Subsequently, the last section is devoted to the prediction frameworks using different classification approaches and standard metrics.

2.1 Tactile-based Remote Phobia Treatment

This section covers two main topics: Phobia treatment and the Tactile Internet domain. We first discuss the concept of phobia, phobia treatment and remote phobia treatment. Afterward, we link the concepts as mentioned earlier to the technological solution for phobia treatment. Next, we will go through the definitions and specifications of Tactile Internet followed by Tactile Internet-related use cases and IEEE 1918.1 Working Group.

2.1.1 Phobia Treatment

Phobia is a type of anxiety disorder that is caused by an excessive fear of an object or situation. According to [15], more than 30 percent of adults in US have experienced a type of phobia during their lives. Nowadays, specific phobia is considered as one of the most common mental health disorders in the world [15]. Based on the Diagnostic and Statistical Manual of Mental Disorders (DSM) categorization, specific phobia is a broad category of phobias and typically include five general categories:

- Fear of animals (i.e., spiders, snakes, dogs, and insects)
- Fear of natural environment (i.e., storm, water, heights, darkness, and thunder)
- Fear related to blood, medical issues and injuries (i.e., injection, fear of dentist and falls)
- Fear of specific situations such as flying, riding an elevator, driving, and enclosed space
- Other types of phobia (choking, loud noises, drowning).

Vivo exposure is an example of a phobia treatment technique in which a patient is exposed to the feared object or situation to conquer their phobia through the therapist’s guidelines [15]. Promising results have been obtained from this kind of treatment. There are other techniques such as Augmented reality phobia treatment, which will be introduced in the next chapter.

2.1.1.1 Remote Phobia Treatment

Remote Phobia Treatment via Virtual Reality is an exciting topic in the telehealth domain, and it aims to extend regular therapy sessions with distant therapists and patients. Remote Phobia Treatment application not only can save much time but also money. It eliminates transportation costs and time as the patient is not required to travel to the therapist's place for the treatment sessions. The patients will also have the possibility of choosing their therapist among a wide range of experts and it also allows the therapist

2.1.2 Tactile Internet

Tactile Internet as the next generation of the Internet enables skill delivery over the Internet and would be an enabler for remote phobia treatment since it promises the ultra-low latency, reliability, and security. It is worthwhile to mention that Tactile Internet incorporates 5G and edge computing and would be the critical enabler for remote phobia treatment. In this section, we first will go through the general definition of the Tactile Internet. Then some main significant use cases of Tactile Internet will be discussed, followed by IEEE 1918.1 Working Group baselines and standards.

2.1.2.1 General definition of Tactile Internet

Tactile Internet is expected to be enabled by The Fifth Generation of the Mobile Communication system (5G) [1]. According to International Telecommunication Union-Telecommunication (ITU-T), 5G services and applications are classified into the following three categories: (i) enhanced Mobile Broadband (eMBB), (ii) machine type communications (MTC), and (iii) ultra-reliable low-latency communications (URLLC). While eMBB aims to provide high rate connectivity, MTC focuses on realizing the emerging Internet of Things (IoT) with its underlying machine-to-machine (M2M) communications. In contrast, by providing low-latency and carrier-grade reliability, URLLC gives way to the so-called *Tactile Internet*, which aims to transmit the modality of touch in addition to the conventional triple-play traffic (i.e., audio, video, and data) [1,4].

The Internet has experienced several big leaps over the decades. As shown in Figure 2.1, it has been converted from a fixed to mobile Internet and then took an evolutionary road to the Internet of Things and now moving forward to Tactile Internet, where goes beyond just allowing communication and collaboration among things. By describing the significant differences between Tactile Internet and IoT in terms of communication paradigm and end devices involved in the

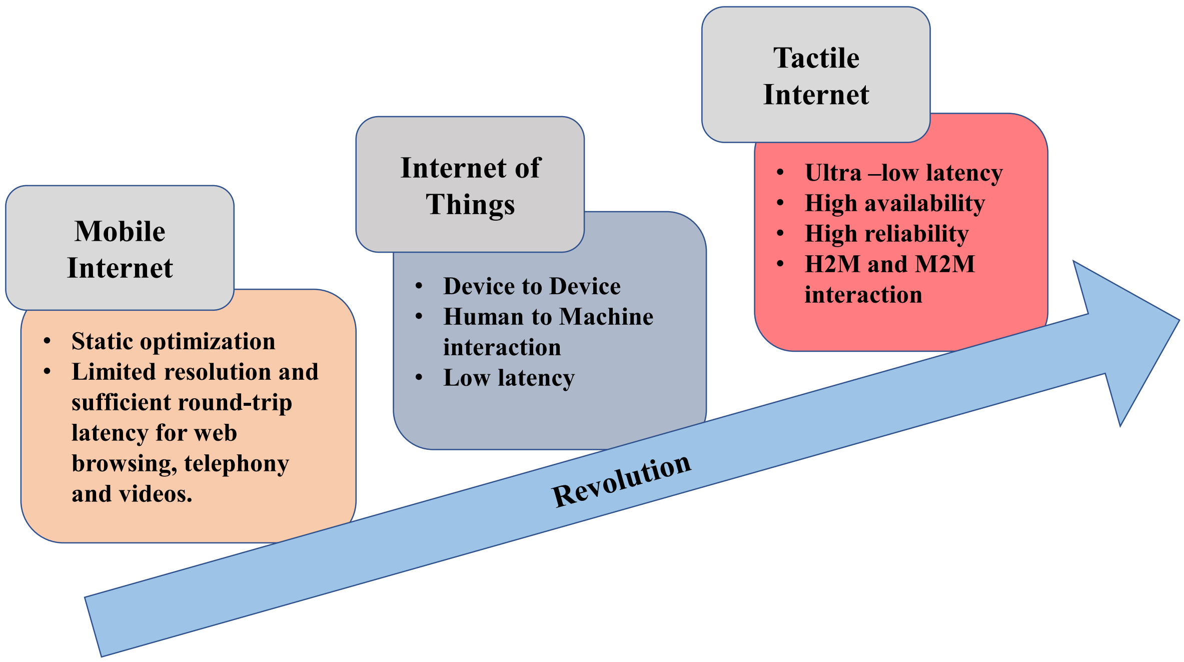

Figure 2.1: Evolutionary road of Tactile Internet.

operation, the functionalities of Tactile Internet will be more comprehensible. The major differences between Tactile Internet and IoT can be described in terms of communication paradigm and end devices involved in the operation. Tactile Internet is centered around the human-in-the-loop (HITL) and nature of the human concept as an enabling end-device. However, IoT considers machine-to-machine (M2M) communication by concentrating on smart-end devices such as actuators and sensors. It is worth mentioning that the concept of IoT is introduced around 25 years ago. However, we are just recently witnessing its popularity in academia and industry. IoT is a relatively new paradigm within which the sensors, actuators, RFID tags, and mobile phones are able to interact with each other and cooperate with their neighbors to reach a common goal [25].

Tactile Internet has addressed two primary requirements which are (1): Ultra-low latency or Ultra-responsive connectivity that is the first critical technical requirement for most of the Tactile Internet applications. The end-to-end latency required for the Tactile Internet use cases is dependent and related to the dynamic of the remote environment and the correlated use case. (2): Ultra-reliable connectivity is another essential requirement for Tactile Internet. Reliability, in general, is measured by the number of packets is received successfully by destination device divided by the total amount of packages which have been sent by the sender. It is worth noting that the ultra reliability is presented by percentage.

2.1.2.2 Tactile Internet Use Cases

Tactile Internet is an emerging technology that enables the real-time delivery of haptic sensation over the Internet by combining machine-to-machine and human-to-machine interactions. Tactile Internet, by empowering the skill/labor delivery over the networks, allows the expert to operate on a remotely-located patient. These possibilities as it presented in Figure 2.2, could revolutionize every segment of the world's economy and society, ranging from healthcare, tele surgery, augmented/virtual reality (AR/VR), education, transportation, commerce, and smart grid systems. Some of the potential applications of Tactile Internet in healthcare, education, and transportation industries will be discussed in the following sections.

The healthcare domain is the most imperative sector enabled by Tactile Internet. Tactile Internet can influence healthcare industry by converting traditional healthcare systems to smart systems by enabling tele-health applications such as telesurgery, telediagnosis and

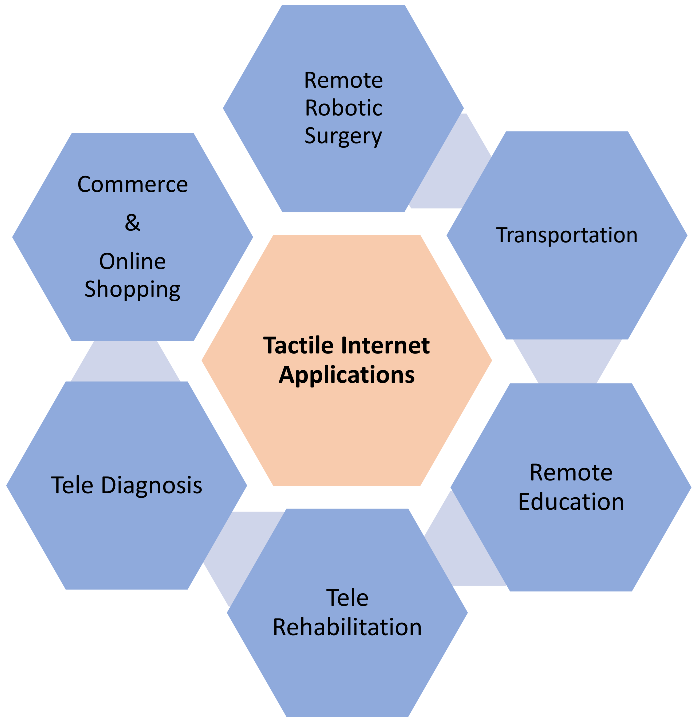

Figure 2.2: Tactile Internet Applications

telerehabilitation. The most common significant influence of all these systems are being time and cost-effective.

During telesurgery, a surgeon supervises robot operation remotely. It can considerably improve surgeon precision and dexterity [26]. Moreover, multiple experienced surgeons are enabled to cooperate during the surgery no matter where they are located. The process of telesurgery will also be beneficial for patients who will experience less pain, blood loss, and tremor. ZEUS, Da Vinci, RAVEN, SOFIE, DLRMIRO, and Al-Zahrawi are some of the available telesurgery systems that have been used for different types of surgery [27]. For instance, Da Vinci (Intuitive Surgery Inc) was introduced in 2000 and is used in many remote robotic surgeries [27]. Reference [1] and [5] discussed a remote robotic surgery system that is based

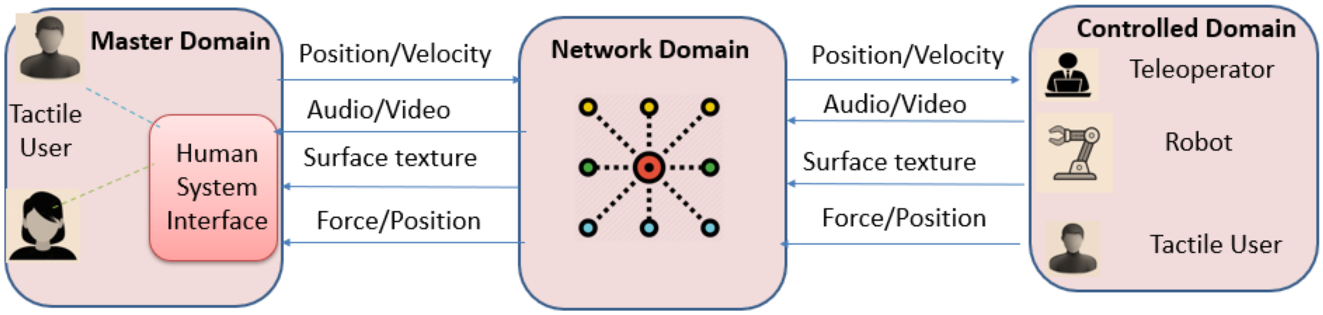

Figure 2.3: A generalized architecture for Tactile Internet Systems.

on Tactile Internet and relies on edge-based architecture. The system is divided into patient side edge domain, surgeon side edge domain, and core network.

In telediagnosis use cases, medical experts can perform the remote controlling of actuators and edge robots for medicine injection. Moreover, in telerehabilitation therapeutic experts assist patients remotely for therapy at home. All the applications mentioned above relieve patients from a costly treatment in-hospital and can access a broader area of experts compared to the traditional in-person treatments. Figure 2.3 presents a generalized architecture of a Tactile Internet system, which mainly consists of a master domain (human operator or tactile user and the human system interface), controlled domain (remotely controlled robot or teleoperator) and a network domain. Transmission of position, audio, video, velocity and surface texture information is viable between master and controlled domain via network domain.

Transportation and autonomous driving are another era where Tactile Internet can have a considerable impact on. We have already put our faith on vehicle sensor applications and driver assistance system to bring more safety and comfortability regarding transportation purposes. However, current communication systems are not fully appropriate for safety needed applications

Figure 2.4: Autonomous Driving and Connected Vehicles

due to the low position accuracy and high communication latency among vehicles (V2V Communications) or Vehicle-to-Infrastructures (V2I communications) [28]. Tactile Internet can be also an enabler for remote driving. Figure 2.4 presents a vehicle to vehicle communication and autonomous driving. As an illustration for autonomous driving, when the weather condition causes the circumstances that driver cannot drive safely, the remote assistance system via accessing the call center will provide remote control of the car. Moreover, through real-time data transmission, a self-driving vehicle could distinguish the objects (e.g., pedestrians, vehicles, and bikes) in real-time. A considerable reduction of traffic and road accidents will be the main advantage of fully automated driving which requires in the order of millisecond end-to-end latency in order to ensure the vehicle safety.

Another economic sector that is influenced by Tactile Internet is commerce. Nowadays, online shopping is prevalent among people. Though, it would be great for a customer to feel the texture of a dress and order a product online by having an awareness of the product texture. The commerce websites can empower their businesses by enabling the reproduction of the exact texture of a fabric that a customer desire. It could bring more customer user experience, which is the goal of every business. The immediate reaction time in Tactile Internet, in addition to interactive elements such as movement simulators, online courses will make it possible for the students and teachers to experience a novel learning environment. Enabling transferring haptic sensation between learner and teacher improve the quality of remote learning procedure. The immediate reaction time in Tactile Internet, in addition to interactive elements such as movement simulators, online courses will make it possible for the students and teachers to experience a novel learning environment.

2.1.2.3 IEEE 1918.1 Working Group

The IEEE "Tactile Internet" standards working group (WG), aims to set the baselines and frameworks to undertake the development of the Tactile Internet standards. According to the emerging IEEE P1918.1 standard working group (formed in March 2016), the Tactile Internet is defined as "*A network (or network of networks) for remotely accessing, perceiving, manipulating, or controlling real or virtual objects or processes in perceived real-time by humans or machines*" [24]. The main aspect of defining the standards in this section is to fully understand the terminologies involved in Tactile Internet interactions, which have been defined within the IEEE 1918.1 WG. Based on reference [24], the authors summarized the core aspects of the Tactile Internet as follows:

1) Tactile Internet not only perceives audiovisual interactions but also it provides a medium for transmitting haptic information over the networks.
2) The haptic, audio, and video communication can be transferred between humans, machines or both humans and machines.

3) The term object is referred to the physical entity. Noting that humans are also considered as objects. Moreover, the term machine is pointing out robots, software, and networked functions or any type of connected entities.

4) Tactile Internet adds a new dimension to the machine-to-machine interactions by considering human-in-the-loop (HITL). During the bilateral teleoperation scenarios, haptic feedback should be transferred remotely when a task is performed. The goal here is that the user should not distinguish the difference between local and remote operation.

5) The assumption is that the result of machine-in-the-loop physical interactions ideally should not differ from when the objects are interacting directly or when the objects are located close together.

6) Haptic communications comprise two categories, tactile and kinesthetic. It can also be a combination of both. Tactile sensation is referred to the touch-related feedback, which is sensed through mechanoreceptors of human skin (e.g., texture and temperature). Kinesthetic feedback provides information about force, torque, position, and velocity, which are perceived by muscles, skeleton and joints of the human body.

7) The term real-time is determined based on the use case and may vary for different types of human and machine interactions.

2.2 Cloud and Fog Computing

This section presents an overview of cloud and fog computing. It first starts with a brief definition of cloud computing. Then, cloud layers followed by a section that discusses cloud computing advantages and features is presented. Next sections cover fog computing definitions, fog computing benefits compared to cloud computing, and fog computing architecture.

2.2.1 Cloud Computing definition

Cloud computing recently attracted enormous attention and gained immense popularity. It is not a new technology rathe a modern operating model that puts together existing technologies (such as virtualization and utility-based pricing) to operate business differently [29]. Cloud computing has been defined through various definitions [30]. It is described by NIST as a “model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction” [31]. Moreover, they defined cloud computing as an integrative concept in [32] by collecting the available description as a “large pool of easily usable and accessible virtualized resources that can be dynamically reconfigured to adjust to a variable load (scale), allowing for optimum resource utilization. This pool of resources is typically exploited by a pay-per-use model in which the infrastructure provider offers guarantees utilizing customized SLAs".

2.2.2 Cloud Computing Layers

Cloud computing has three main facets: Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service. The lowest layer is the IaaS and PaaS seats in between the two layers on top of the IaaS. PaaS provides a software environment for application development, and management. SaaS provides software applications to the end-users [7].

i. **Infrastructure-as-a-Service:**

IaaS provides on-demand virtualized services, including computing, storage, and communication [8]. The IaaS consists of physical and virtualized infrastructure resources (e.g., network, storage, and servers). Moreover, this layer offers customers flexible and cost-effective services. It relies on virtualization, which allows the service to abstract hardware resources. This layer has the lowest abstraction grade where users can access the infrastructure via the Virtual Machines (VMs). At this stage, users request IaaS Provider computing resources such as processing power, memory, and storage and then use the resources to deploy and run. The IaaS consists of physical and virtualized infrastructure (e.g., network, storage, and servers) and provides the customers with flexible and cost-effective services. Amazon Elastic Compute Cloud (EC2), Microsoft Azure, Google Compute Engine, OpenNebula, IBM Blue Cloud and Rackspace are some examples of cloud IaaS.

ii. Platform-as-a-Service (PaaS):

The PaaS provides the requisite framework to enable the application provisioning lifecycle. The PaaS provisioning life cycle comprises the development, testing, deployment, and execution. Moreover, this layer offers a higher level of abstraction compared to IaaS, which allows the developers to make the cloud programable. Microsoft Azure, Cloud Foundry, Google cloud platform, Aneka are examples of PaaS.

iii. Software-as-a-Service (SaaS):

Tactile Internet is being offered as SaaS in cloud computing. This layer is a software delivery model which is located at the highest level of cloud architecture. Web portals are the medium for end-users that can access the service provided by this layer. The software which is offered by the software vendors at this layer will run on the infrastructure and platform. The users are not forced to own the software, yet they can pay for the certain use of elements. Google Docs and Salesforce, Dropbox, BigCommerce, Cisco WebEx, SAP Concur, and GoToMeeting.

2.2.3 Cloud Computing Advantages and Features

Cloud computing has several advantages and features. Cloud computing's primary characterization is multi-tenancy, scalability, elasticity, pay per use, and rapid provisioning of applications and services [7]. The essential features of cloud computing are described below.

- **Elasticity**: Cloud computing enables the opportunity of having infinite computing resources on-demand. Therefore, resources are available to users in any quantity at any time [29]. A customer can obtain more resources based on his/her needs. Moreover, a customer can release the resources that are not needed anymore [33].
- **On-demand Self-Service**: Resources can be available based on the user's needs at any time. There is no need for a user to contact the cloud provider for accessing the resources.
- **Scalability**: Services offered by cloud are easily expandable to a large scale based on the user demands. The rapid increase of service demands, and rapid provisioning of resources can be handled by cloud computing Scalability an elasticity let the dynamic provisioning and de-provisioning of resources that are in demand.
- **Multi-Tenancy**: Multi-tenancy enables the co-existence of several applications on the same underlying infrastructure and sharing the resources in an isolated manner. Multi-Tenancy is also called resource pooling, which lets multiple users access the shared pool of resources. For instance, several virtual machines that belongs to various users can be hosted by a physical server [33].

- **Per-Usage Billing:** The flexible pricing and pay per use basis is another significant feature of cloud computing. Indeed, users will pay based on their utilization of the resources. For instance, each cloud provider can charge a user based on his/her user usage of a virtual machine.

2.2.4 Fog Computing Features and Specifications

Although cloud computing offers elasticity and scalability, still encounter latency problem due to the distance between cloud and end-user [7]. Moreover, failing to provide real-time services usually will lead to network congestion and quality of service degradation. To address the limitations of cloud computing, the fog computing paradigm is introduced by Cisco.

Fog computing is not an entirely new concept, it is instead an extension of cloud computing. The relevant concepts, such as cloudlet and Mobile Edge Computing has been introduced before fog computing. Fog indeed cannot perform in a standalone mode, and it should be accompanied by a cloud. This interaction would drive specific attention to the link between these two important paradigms [34].

2.2.5 Fog Computing Advantages

Fog computing offers several advantages compared to its ancestor cloud computing. Cloud computing uses fog computing to enhance usability and accessibility in various computing environments. The main characteristics and advantages of cloud computing offers are elaborated below and some of the main characteristics and differences of cloud and fog computing is presented in Table 2.1.

One of the main characteristics of fog computing is its capability to support the applications and scenarios that necessitate low-latency and mobility. This capability is viable through the fact that the fog computing systems are positioned very close to the end-users in a distributed manner. Therefore, Fog computing provides shorter communication paths, quickening automated analysis, and decision-making procedures. Moreover, Fog computing has been converted as an urging need of individuals and organizations due to its tremendous advantages such as real-time service provisioning and support of mobile users. Also, there is availability for IoT devices and end-users to be available offline. Geographical distribution, low network congestion, and low power consumption is another advantage of fog computing as it reduces the traffic between end-devices and the cloud. Data security is another significant feature of fogging. When local networks are preprocessing data, security-sensitive data can remain internal or being encrypted before uploading it to the cloud. As a final point, fog computing emerges cost-effective through utilizing third-party networks while the network providers tolerate high charges for offering a high-speed upload to the cloud.

2.2.6 Fog Architecture

Fog computing can bring certain added value to the cloud and the cloudlet paradigm. For instance, the cloudlet presents a three-tier hierarchy as its architecture. However, fog provides more flexibility to the system by offering an n-tier hierarchy/architecture. [35], [36]. Besides, fog computing offers a life cycle management of applications which are expanded over the n-tier fog architecture via “Fog Service Orchestration Layer” [35]. Figure 2.5 demonstrates a fog architecture with a three-tier/strata system and then presents each stratum specification, including the Cloud layer, Fog layer, and End-user layer.

Table 2.1 Main features comparision of conventional cloud and fog computing.

Features	Cloud Computing	Fog Computing
Latency	High	Low
Distribution	Centralized	Distributed
Applications	Delay tolerant and computation incentive	Latency Sensitive
User Devices	Computers	IoT and smart wearable devices

- **Cloud layer:** The cloud layer is the topmost tier of a typical fog strata architecture. Data warehousing and big data analytics are done in this layer since all the cloud data centers, cloud servers and storage devices for the purpose of broadcasting, and high-performance servers are located at this layer.
- **Fog Layer:** The fog stratum/layer is the intermediate tier between cloud and user layer can be designed by one or more fog domains. Different or identical fog providers are able to control the fog domains. Moreover, each fog domain can be presented in the form of

composing edge routers, switches, gateways, set-top boxes and proxy servers, etc. Fog enables computing at the edge of the network, closer to end-user devices. These nodes can have storage capabilities as well as computational abilities. Moreover, Local Area Network (LAN) is responsible for the communication among fog nodes and end-user devices (i.e., IoT devices). On the other hand, the Wide Area Network (WAN) is the media for communication between cloud nodes and end-user devices.

- **End-Users Layer:** The lowest tier of the fog computing architecture is the end-user strata/tier. The users are allowed to access the data via the fog nodes and networking devices that are located in decentralized and localized information centers. However, if the fog cannot provide the required data for the user, then the user will acquire/ask data from the cloud server and will directly access the cloud storage.

2.3 Fog- based Architecture for Remote Phobia Treatment

In this section, we first elaborate on the remote phobia treatment system proposed in the Tactile Internet domain in Section 2.3.1, and then a Remote Phobia Treatment architecture followed by functional entities will be discussed in Section 2.3.2.

2.3.1 Remote Phobia Treatment via Virtual Reality

Recently, a remote phobia treatment via the virtual reality system is proposed as another interesting approach of Tactile Internet, which is viable through the real-time delivery of haptic sensation over the Internet [23]. Tactile Internet enables skill delivery as well as the exchange of conventional audiovisual and data content over the network with promising factors such as ultra-low latency and reliability by incorporating 5G networks and edge computing.

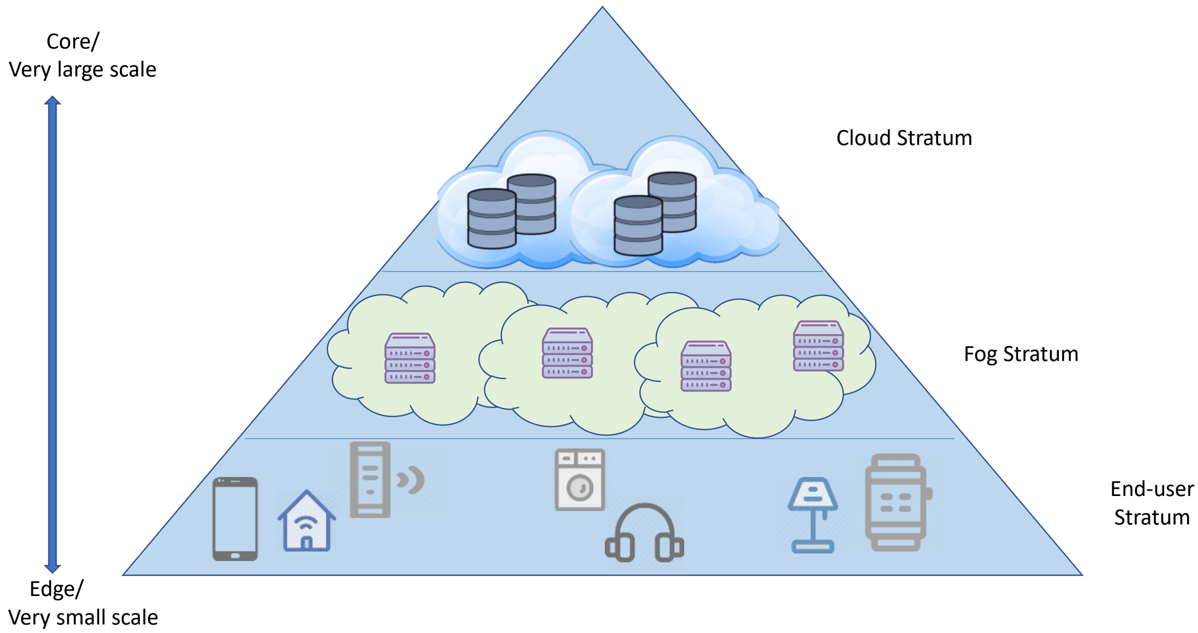

Figure 2.5: Fog Computing Architecture.

Phobia treatment via Virtual Reality is a greenfield in the telehealth domain. It aims at replicating regular therapy sessions with distant therapists and patients. It not only can save much time, but it is also cost-effective. It eliminates transportation costs and time as the patient is not required to travel to the therapist's place for the treatment sessions. Moreover, it allows patients to choose the most appropriate experts for their treatment without any distance uncertainties. Moreover, remote procedure allows the therapist to have therapy sessions for multiple patients at the same time and with the same quality. Equipment such as VR headsets and wearable haptic devices (i.e., gloves) in VR make virtual reality more immersive.

The end-to-end latency requirement plays a significant role in delivering an appropriate quality of experience to the users. In the case of remote phobia treatment, if the haptic packets do not reach on time to the users (50 ms), then the system will experience the quality of experience degradation.

2.3.2 Fog-based Tactile Internet Architecture

In this section, our considered fog-based VR phobia treatment system architecture is presented followed by the functional entities, specifications and correlated responsibilities.

2.3.2.1 Remote Phobia Treatment Architecture

The overall end-to-end architecture for the Tactile Internet is divided into three main domains: master domain, network domain, and a controlled domain.

- **Master Domain:** A master domain normally refers typically to a human (operator) and a human-system interface (HSI). The HSI can be a haptic device called a master robot that translates the human actions to tactile input via different tactile coding procedures. The haptic device lets the operator (e.g., Surgeon) touch and manipulate the objects in the real and virtual environments while the master domain can control and lead the remote operation.

- **The Controlled Domain:** The controlled domain, which is also called the slave domain, may refer to a teleoperator or a controlled robot that is being controlled by the master domain via several command signals. The teleoperator interacts with objects in the remote environment. Energy is exchanged between the master and controlled domains through command and feedback signals, thereby closing a global control loop.

- **Network Domain:** The network domain provides the medium for bilateral communication between the master and controlled domains, kinaesthetically coupling the human to the remote environment. Ideally, the operator shall be completely immersed in the remote environment.

Figure 2.6 illustrates the generic architecture of the considered haptic-enabled VR remote phobia system, which consists of three main particular domains: (i) therapist, (ii) patient, and (iii) cloud infrastructure [23]. Through the architecture shown in Figure 2.6, patient and therapist are able to communicate with each other remotely via exchanging audiovisual and haptic information in real-time. All the entities that exist in the therapist and patient domains are located at the network edge to help meet the URLLC requirements of the Tactile Internet.

For the animal phobia treatment use case, both therapist and patient are equipped with haptic-enabled gloves along with VR headsets. In our considered VR system, hand-tracking devices at the therapist's end is responsible for detecting the therapist's hand motion on the given VR coordinate system. Further, haptic-enabled gloves at both ends provide the therapist and patient with haptic feedback through the Internet. It is worthwhile to mention that in this thesis; the virtual reality environment is divided into multiple regions named zones.

Each zone represents a specific part of the phobic animal with zone NULL denoting the outside of the phobic object. We note that associated with each zone, there is a pre-defined haptic feedback/sensation. The shown architecture in Figure 2.6 relies on representational state transfer (REST) to let the architectural components communicate over the hypertext transfer protocol (HTTP). REST is a way to reunite the programmable web with the human web. RESTFul web services are accessible for clients to use. REST relies on HTTP and inherits its advantages, mainly Statelessness, Addressability and Unified interface.

The fog domain at a given therapist or patient side comprises the following five main entities: (1) *haptic device manager*, which is responsible for handling and coordinating between the system and end-user device, (2) *zone detector*, which continuously updates the VR component with the therapist's spatial hand movements by detecting the location of the therapist's hand in VR, mapping the spatial information to the VR environment, and then sending it to the feedback generator, (3) *feedback generator*, which is responsible for generating the haptic feedback using predefined vibration patterns based on the information received from zone detector, (4) *VR component*, which not only provides the VR view for multi-sensory (i.e., audiovisual, and haptic) interaction between the participants, but it also interacts with the VR headset and provides the synchronization once the actions take place, and (5) *conferencing server*, which allows both therapist and patient to commence a new connection when they are willing to start a new therapy session. It is worthful to mention that the phobia treatment architecture let the users to exchange the visual, auditory, and haptic information.

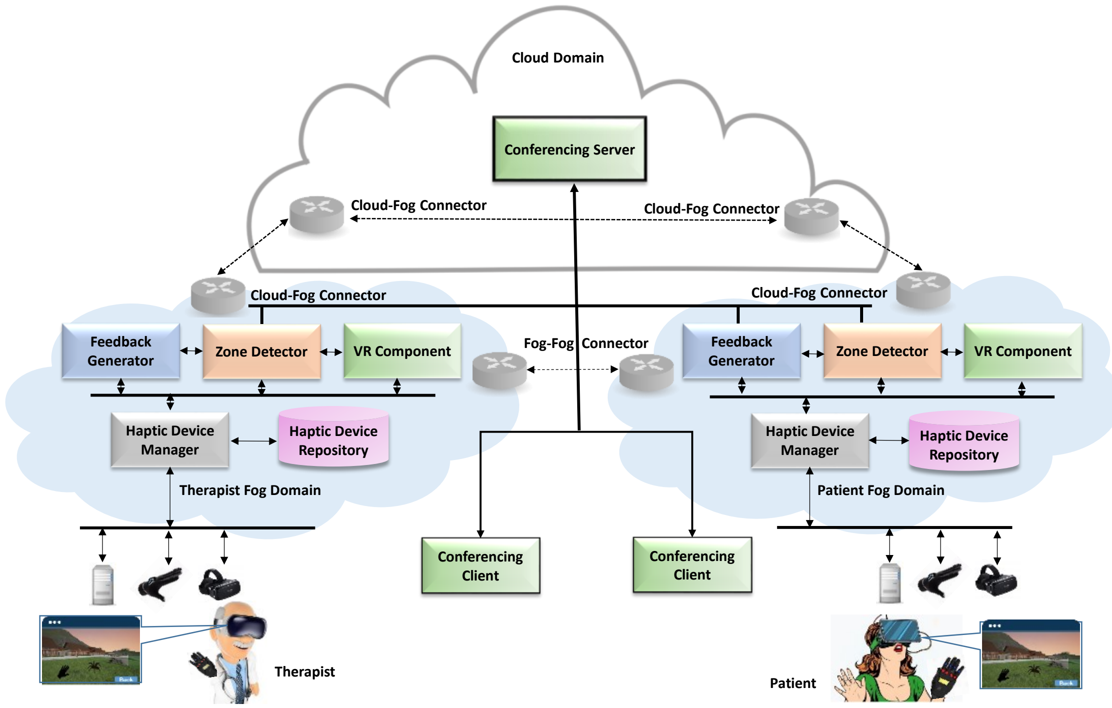

Fig 2.6: Generic architecture of our haptic-enabled VR remote phobia treatment system [23].

2.3.2.2 Functional Entities

This section presents the main components functionalities and characteristics of the fog based remote phobia treatment architecture, which will consider the definitions in the paper [23]. Moreover, the information is needed for each component will be discussed, followed by the possible interactions with other components through architecture. There is a need to define uniform interfaces to receive and provide information to other components to have an appropriate communication view between architectural components.

- **Zone Detector**: Provides the information related to the spatial information in VR coordinate system. Moreover, mapping the spatial information to the location of therapist hand is another main responsibility of the zone detector. Afterward, it passes the information related to the therapist's hand spatial information to the feedback generator. Zone detector should get notified about any possible changes in spatial information of the tracked object (i.e., hand). Indeed, it subscribes to the hand tracking device through the haptic device manager component. To elaborate more on the functionality of the zone detector, let's consider an example of communication between zone detector and other components in the architecture: the zone detector obtains the therapist's hand location/position from the hand tracking device. Afterward, the Zone detector translates/transfer the spatial information received from the hand tracking device to the VR component. As the final step, the zone detector will map the virtual hand location to the zones and then transfer it to the feedback generator.

- **Feedback Generator:** The feedback generator is directly communicating with the haptic device (e.g., haptic glove). The feedback generator's primary responsibility is to generate the correlated feedback on the information received from the zone detector. As the feedback generator receives the zone information from the zone detector it maps the zone information to the dedicated feedback and then generates the correlated/appropriate tactile feedback. The feedback should be generated as soon as possible, and the correlated haptic feedback should be generated as realistic as possible. This means that the generated vibration through Gloveone should stimulate vibrators to make the effects similar when touching the same objects.
- **VR Component:** The VR component is responsible for communicating with the VR headset while it must provide the synchronized virtual reality view as the action takes place. The action takes place when the physical hand is moved and tracked by the hand tracking device.

- **Haptic Device Manager*:*** The haptic device manager is the central point between the system and end-user devices such as haptic devices (e.g., haptic glove). Moreover, haptic device manager can provide a unique interface in order to enable communication with the haptic devices.
- **Tactile Device:** The tactile device can be considered as the core element of any tactile edge. The tactile devices functionalities highly depend on the considered Tactile Internet application. It consists of a system of sensor nodes and actuator nodes that are entities with sensing, actuation, and some sort of processing capabilities. Considering the sequence of events and the use case scenario that has been proposed, we should note that the zone detector at the therapist side domain, communicates directly with the feedback generator and the VR component at the patient's side domain.

2.4 Prediction Frameworks

In this section, machine learning definition, categorization and a brief description of each subcategory have been demonstrated, followed by a brief description of the practical classical machine learning classification approach in Section 2.4.2.

2.4.1 Machine Learning-based Prediction Methods

Machine Learning is a great solution for solving complex problems that are not approachable by traditional methods. As it is presented in Figure 2.7, machine learning is divided into three subcategories based on the level of supervision, type, and volume of the data. Figure 2.7 shows the fundamental differences between these three categories in terms of input and output data.

Supervised learning tries to find a pattern among data available and apply it to an analytic process [13]. In supervised learning, predicting, or solving the problem is viable through considering several examples of random vector and its label value, and the result is an estimation of the probability or properties of a distribution. As an example, a supervised machine learning technique can identify a specific animal, or an object based on the available images and written descriptions.

In unsupervised learning as opposed to supervised learning, no training samples or labels are available, and a considerable amount of data is required. The algorithms try to find a suitable pattern among data and then the similar data points will be clustered together [37].

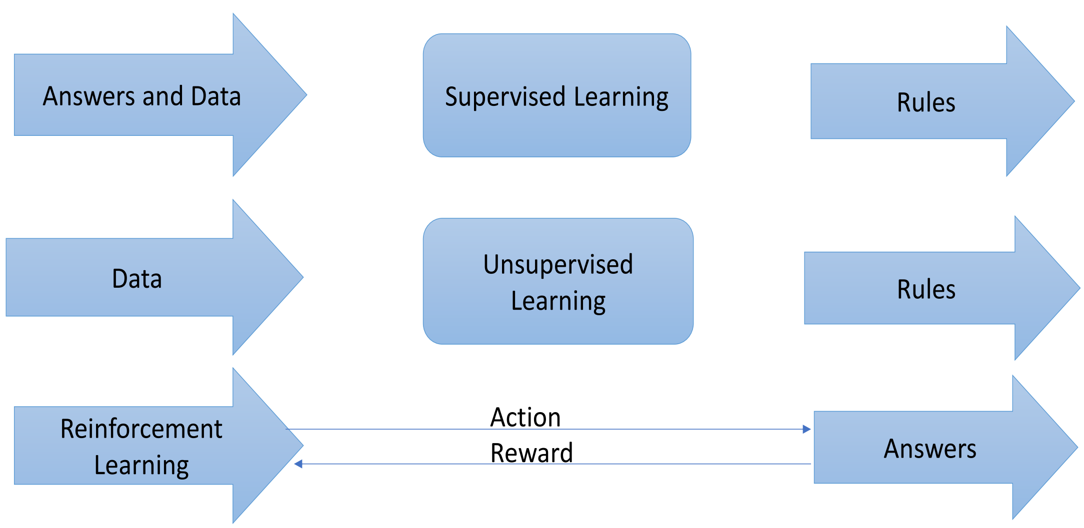

Figure 2.7: A comparison between machine learning techniques (a) Supervised Learning, (b) Unsupervised Learning, and (c) Reinforcement Learning.

Moreover, Unsupervised learning can be applied for execution of the wide range of tasks related to points including clustering, features extraction, features classification, distribution estimation, and distribution specific samples generation [12].

Reinforcement learning is the third method that performs based on interactions with the environment. There are different paths for an agent, and it gets feedback based on the experiences in terms of rewards and penalties faced during the process. The learner should realize which action would bring the best rewards since there is no guidelines through choosing actions.

Generally, supervised machine learning techniques empower solving two types of problems named classification and regression [12]. As it is discussed in Chapter 1, classification methods try to identify the class or labels that a sample belongs to. A *sample* is referred to an entity, data or an observation needed to be labeled. The key features which are parameterized in a vector of a sample selected are the input of the classification techniques, and the result of the classification is presented as discrete values that demonstrate different classes or labels. It is worth mentioning that the data set using in classification approach may be bi class or multi-class. The binary classification classifies the tasks to no more than two classes and multi classification classifies the instances to one of more than two classes.

Regression techniques are widely used to predict the continuous values which will then fit the curves [32]. Regression analysis is widely used in estimating the dependent values in finance, economics and capturing the trendlines especially for analyzing the trends for investment approach. K- Nearest Neighbor, Logistic Regression, Support Vector Machine, Decision Tree are the most applicable techniques in supervised learning approach, which are used based on the problem need to be solved. Various machine learning applications are related to the tasks which can be considered as supervised learning and, in this thesis, we have concentrated on the concept mentioned above. Particularly in this work, the classification approach is mostly considered while the data is discreet and unorder values.

2.4.2 Classification Techniques

In this section, some of the classifiers mostly applied for solving supervised classification problems are introduced. Classification is the process of assigning samples to predefined categories based on the characteristics of the samples. Samples in a category will be remarkably similar to each other compared to a sample in another category.

2.4.2.1 K - Nearest Neighbor Classification Technique

*K*NN is one of the most accurate, simplest, and important methods for solving both classification and regression problems and it is ranked as one of the top ten most practical and influential machine learning algorithms [9]. *K*NN is applicable in many fields such as artificial intelligence tasks (i.e., pattern classification and recognition), data mining, computer vision, and bioinformatics by its ability to produce simple but powerful classifiers. Each unlabeled example will be classified based on the majority voting in k-nearest neighbors which are presented in the training data set. Despite its simplicity, *K*NN mostly produces competitive results compare to another machine learning algorithms. For a better understanding on the functionalities of *K*NN as the supervised classifier, consider that there exists a set of training data that have been assigned labels and the classifier do memorize the observations through labeled test set data. Therefore, when given the sample x, the *K*NN algorithm, it first recognizes the k nearest neighbors related to training samples and then perform the prediction for new and unlabeled observations. When the observation's value is similar to each other, then the probability of classification with the same label enhances. Despite its simplicity, *K*NN mostly produce competitive results compare to other machine learning algorithms.

2.4.2.2 Weighted K-Nearest-Neighbor

WKNN classifier made an improvement on the traditional nearest neighbors' approach. While the KNN approach neglects the influence of nearest neighbors, the intuition behind Weighted KNN classifier is assigning greeting significance/ higher weights to the points which are closer to the unclassified sample. Accordingly, fewer weights will be assigned to the points which are farther away. When the focus comes to the classification based on weighted nearest neighbors, it would usually achieve a better classification performance than the standard *K*NN approach.

2.4.2.3 Naïve Bayes Classifier

The naive Bayes classifier is considered as one of the key multi-class classification approaches, where all the features are temporary and directly connected to classes with the so-called conditional freedom rule. Naïve Bayes classifies based on the Bayes "theorem" and it performs based on an assumption that each class attribute is independent to the value of other attributes. It is normally said that the accuracy achieved by this method is not high enough compared to other methods. However, it has a high-speed performance. Moreover, it has an appropriate tolerance to missing values. Short computational time in training process is the main advantage of Naïve Bayes method

2.4.2.4 Logistic Regression

Logistic regression is a classification technique that yields probabilistic outcomes of the observed data according to a given maximum likelihood argument [38]. Logistic regression categorizes the observations to a discrete set of classes. There are two types of logistic regression:

(1): Binary logistic regression, which classify the classes to two based on the probability that a new observation belongs to a particular class. For instance, classifying an email to spam and non-spam or classifying the online transactions to fraud and non-fraud. (2): Multinomial logistic regression which categorizes the data to more than two possible discrete outcomes. As an example, classifying the animals to dogs, cats, and horses.

2.5 Conclusions

In this chapter, we discussed the background concepts related to this thesis. We first introduced the concepts related to tactile-based remote phobia treatment, including explaining the phobia treatment approaches and Tactile Internet-related domains. Then, we followed by discussing the cloud and fog computing paradigm, explaining the cloud computing definitions, layers, advantages, and features. Moreover, in this section, fog computing definition, features, and architecture are discussed. Afterward, focused on the fog-based architecture explaining the functional entities for remote phobia treatment. Finally, the prediction frameworks explaining different classification approaches and standard metrics are discussed.

Chapter 3

Use case and State of the Art

In this section, we first present our considered fog-based VR remote phobia treatment system and then explain the motivating scenario and problem statement. Subsequently, the requirement that is derived from the motivating scenario will be discussed in the next section. Afterward, we review prior research work related to the phobia treatment. After presenting an overview of the pertinent works on VR-based phobia treatment, the applications of predictive frameworks, and machine learning in the Tactile Internet era, we review and evaluate state of the art based on the derived set of requirements.

3.1 Use case and Problem Statement

In this section, after briefly presenting our considered fog-based VR phobia treatment system architecture and its functional entities, we elaborate on the problem statement using an illustrative example. In the previous chapter, we mainly described the generic architecture for the considered haptic-enabled VR remote phobia system. The architecture consists of three main domains named: patient and therapist fog domain and cloud infrastructure [18]. Moreover, the architecture design enables the patient and therapist to communicate remotely through audiovisual and haptic information in real-time. The architecture design enables the patient and therapist to communicate remotely through audiovisual and haptic information in real-time. In order to meet the ultra-low

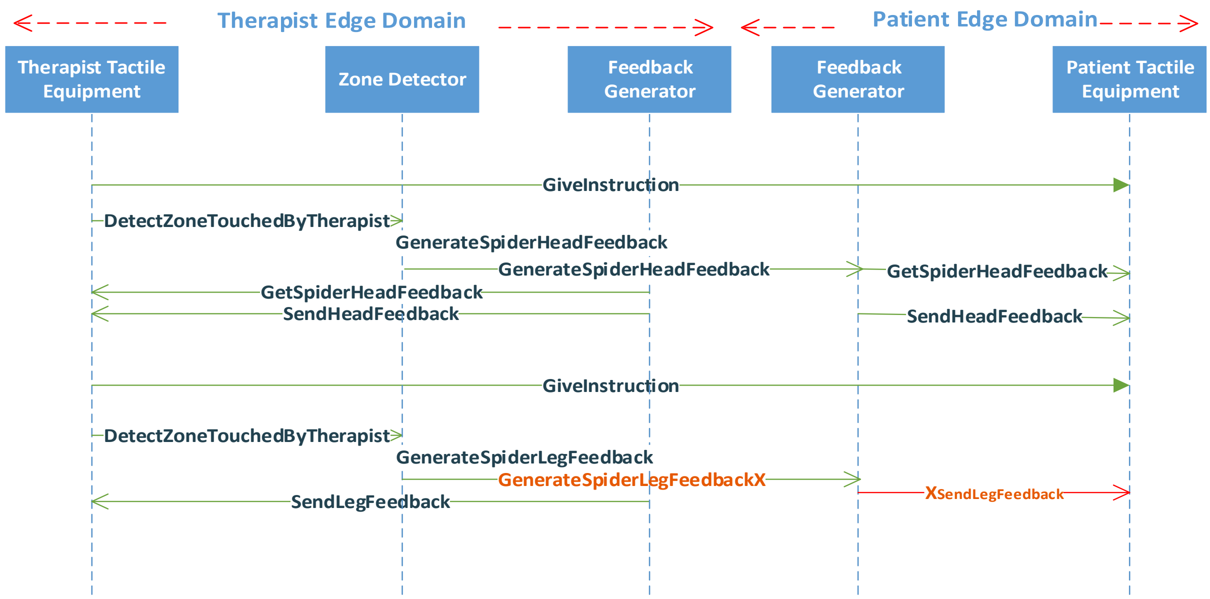

Figure 3.1: An illustration of the high-level sequence diagram of the communications between the therapist and patient.

latency requirement of Tactile Internet applications, all the entities in the architecture are positioned at the edge of the network.

Let us consider a therapist, located at a remote hospital, which is intended to interact with a phobic patient using VR exposure therapy through a shared haptic-enabled VR environment. We consider the following two scenarios. In the first scenario, we assume that the underlying networking infrastructure is able to provide stable and ideal connectivity between the different entities of the VR phobia system shown in Figure 3.1, as opposed to the second scenario, where the communication-induced artifacts (e.g., latency and jitter) exist. It is worthful to mention that the first scenario will discuss the ideal haptic transmission between therapist and patient fog domains where the haptic messages will reach to the patients' fog domain in real-time. However, the second scenario will elaborate a more realistic haptic data transmission between two different fog domains by considering loss/delay in data transmission process.

Figure 3.1 illustrates the sequence diagram of the two scenarios in the process of remote phobia treatment. In scenario 1, when the therapist attempts touching the virtual spider in VR, the zone detector in the therapist fog domain detects the touched zone of the therapist hand in VR. Next, the zone detector maps the spatial information to the specified zone and then sends the identified zone to both therapist and patient feedback generators. When the feedback generators in both therapist and patient edge domains receive the zone/spatial information, they execute the required action and generate the corresponding haptic feedback, which is then forwarded to the patient and therapist tactile devices in real-time. Upon receiving the haptic feedback, the therapist edge domain sets a timeout. The timeout is defined as the time between the detection of the zone until the reception of the haptic feedback by the patient edge domain. In scenario 2, the corresponding haptic feedback fails to reach the feedback generator at the patient's side within the given threshold (i.e., 50 ms in our case). We note that the second scenario presents a more realistic case, where communication-induced artifacts such as delay, and jitter may incur an excessive amount of delay (or even loss) to some of the haptic messages. To be more specific, if the patient does not receive any haptic message within a given threshold, she may lose togetherness and immersion. This, in turn, may have a negative impact on her QoE. In the following, we aim to leverage a predictive mechanism, that provides the patient with the predicted haptic messages in the case of loss and/or delayed messages.

Based on the discussion above, we can reach to the fact that there is a need to design a mechanism to cope with the delayed/lost haptic feedback problem. Towards this end, we propose our predictive framework called ETL, which will be discussed in the next chapter. The framework is an essential aspect of remote phobia treatment, particularly when the patient edge domain identifies excessive delay or packet loss.

3.2 Requirements

According to the scenarios discussed above, two main requirements should be considered in the remote phobia treatment scenario. Satisfying the requirements will describe in this section, would probably result in high quality of user experience.

3.2.1 Ultra-Low Latency

Ultra-low latency or Ultra-responsive connectivity is the first key technical requirement needed to be addressed in the remote phobia use case scenario provided in Section 3.1, and it is highly correlated to the end-to-end delay. The prediction related to the described use case scenario in Section 3.1, should be done within an acceptable delay (50 ms) to ensure the timely delivery of the haptic messages (real-time haptic interaction). If the prediction performed by ETL comes too late, it would be useless to predict the therapist's hand movements.

It is worth mentioning that the end to end latency required for the Tactile Internet use cases depends on the dynamic of the remote environment. For example, When the users are experiencing a highly dynamic setting for a use case such as a tele-soccer game, it is considered as time-critical application latency required for this use case is between 1 to 10 ms. For teleoperation systems such as telesurgery and telerehabilitation, which perform in a medium-dynamic environment, the latency requirement is 10-100ms [24]. Finally, for static environments such as tele maintenance the latency requirement has been measured between 100ms and 1s [24]. Noting that the end-to-end latency is defined as the transmission times take when sending the information from source to destination device which include the processing time at different communication devices (e.g., routers, switches) and various servers and the retransmission time through communication infrastructure which convey the information to end device or human. (in millisecond). Communication between patient and surgeon during remote robotic surgery should be fast and reliable since the system needs to ensure about the necessity of stability of real-time interactions between patient and surgeon. Noting that the surgeon actions will be translated to a control message and will be sent to the surgical robot. Afterward, the surgical robot will perform the patient's actions if the communication experiences a delay due to the core network issues. Otherwise, the surgeon may notice a time lag between their actions and the corresponding feedback.

Considering all the examples and definitions, the realistic experience of VR will occur by avoiding cyber-sickness, which will be avoided by ultra-responsive connectivity. Cybersickness arises when the multiple senses (audio, video, and touch) contributing to communication, but the response/ feedbacks of the different senses are unsynchronized to the time-lag exists between visual and tactile sensation [40].

3.2.2 Ultra-Reliable Connectivity

Reliability, in general, is defined as the number of packets is received successfully by the destination device divided by the total amount of packets which has been sent by the sender which, is presented by percentage. According to reference [40] and [41], mission-critical 5G applications in the era of Tactile Internet such as telemedicine, telesurgery and remote driving require a high availability of 99.999 percent.

The prediction of the proposed Edge Tactile Intelligence (ETL) should be accurate. Precise methods such as machine learning techniques for providing high rate prediction accuracy is needed. Providing accurate haptic feedback would help the patient and therapist experience a more realistic VR Tele phobia treatment environment.

3.3 State of the Art

In the subsequent section, after presenting an overview of the pertinent works on VR-based phobia treatment, we discuss the recent studies on the application of machine learning in the telehealth domain and the related-Tactile Internet applications (e.g., VR, teleoperation). In each section, we evaluate and summarize the proposed framework in the current state of the art. It is worthful to mention that some of the works in the literature have not addressed the requirement of our proposed framework. Therefore, the requirements are discussed in a separate section.

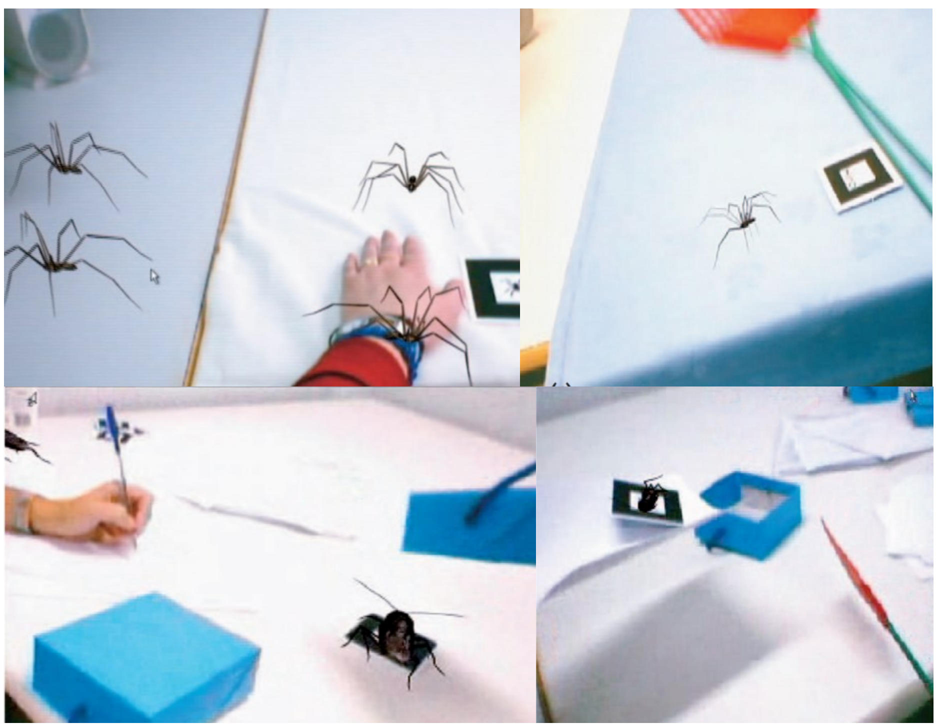

Figure 3.2: Exposure session steps for spider and cockroach [44].

3.3.1 VR Phobia Treatment

Recently, virtual reality (VR) for phobia treatment has gained much attention. Through this technique, the therapist tries to cure the phobic patient by gradually exposing her/him to the feared object (e.g., spider) [42]. This section first discusses the fears of small animals and debates that the mentioned fear mostly remains until the adolescent stage, which later may cause a phobia. Traditional treatment of small animal phobias is along with the exposure to the real animal. Though, due to the threatened feeling of the real animal, it may bring patient resistance and accordingly, therapy abandonment. Therefore, taking advantage of intelligent environments such as virtual reality would be an alternative that allows the therapist to support a phobic patient through virtual, gradual, and, at the same time, controlled exposure of the patient to the animal. Virtual phobia therapy lets the patient gradually be exposed to the non- real feared object [42].

To date, several works have examined the feasibility of using VR for the treatment of spider and cockroach phobia due to advantages and the proven result of using VR and augmented reality (AR) toward psychological disorders [15], [21], [43], [44]. AR-based phobia treatment is also a type of exposure therapy, which allows the patient to see the phobic object in the shape of a virtual object in the real world [44].

Paper [44] presents an augmented reality system to treat the fear of spider and cockroach phobia. The authors have built two virtual models for the mentioned insects. They defined different sizes and movement patterns (e.g., dead, moving, or static). One of the distinguishing features of reference [44] presented in Figure 3.2 is that participants experience multiple exposure steps. During the therapy session, patients are exposed to spiders and cockroaches in different scenarios. For instance, spiders cross over the patients' hands, or patients are able to kill the spiders with a flyswatter. The last scenario is picking up a dead cockroach and putting it into a box.

Through the proposed paper in [44], the patient can even kill the insects, and she is able to see the insect crossing on her hand or leg. The proposed methods in [15], [21], [40], [43], and [44] are not cloud or fog based but mainly are appropriate for desktop or mobile devices. Moreover, non-of the authors mentioned above considered the remote procedure in treating patients and the latency issue in their work. Additionally, their proposed frameworks do not allow the exchange of audio, visual, and haptic information in real-time.

In paper [18], the authors designed and developed a haptic smart environment for adolescents with mobile technology use. They have reported that 12.5% of the general population suffers from a small animal phobia, with 5% being teenagers. Moreover, based on a survey conducted among 120 adolescents and between 74 animals, the five top feared animals have been claimed as Figure 3.3 The authors have also claimed that the spider is ranked first among all the small animals in terms of the level of anxiety induced for the adolescent. The authors claimed that the size and movement level of animals can affect the phobia level of adolescents. The authors in paper [21] argue that the size and the movement level of a small animal in VR should be adjustable, which in turn may influence the patient's level of fear toward a small animal.

Some papers have developed systems for treating other types of phobias, such as fear of height, which is also known as acrophobia [21], [42]. Paper [42] stating that the Augmented Reality which is a branch of virtual reality and has been proven operative for curing phobias.

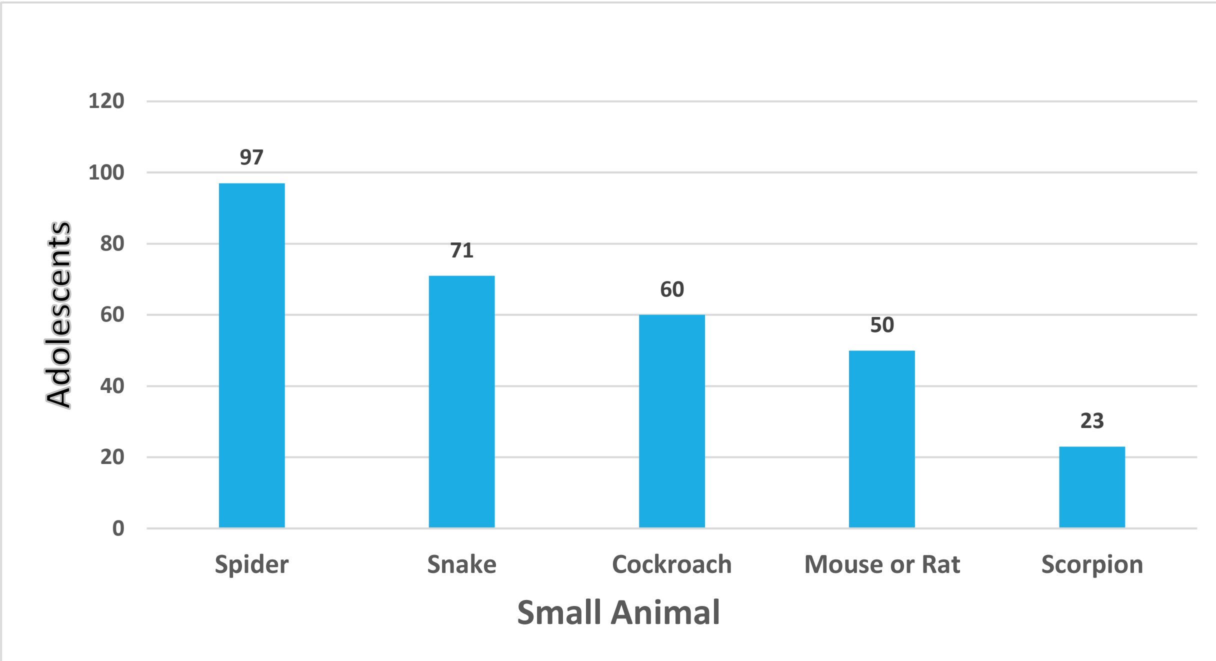

Figure 3.3: Most feared animals based on 120 surveyed adolescents [18].

VR exposure therapy has been proven beneficial in treating fear of flying, claustrophobia, eating disorders, and post-traumatic stress disorder, fire, airplane, and public speaking [43, 44].

It is worthwhile to mention that non-of the papers mentioned above did consider the remote treatment approach and transmission of haptic messages by considering audiovisual and haptic feedback transmission. Therefore, the latency and accuracy requirement and the Tactile Internet aspect of the Phobia treatment procedure are not fully addressed.

Reference [23] was the first work to focus on a cloud-based remote phobia treatment system. The proposed architecture in [23] is based on the systematic exposure therapy, which aids the therapist to cure the phobic patient by gradually exposing her to the feared object (i.e., spider) in the virtual environment. Both the therapist and the patient are able to communicate through

Table 3.1: The main contribution works related to VR phobia treatment and Machine learning in Tactile Internet.

Category	Essential Features	Differences compared to our proposed framework
Animal Phobia Treatment Systems [15], [21], [40].	- Using VR and AR systems toward small animal phobia disorders Gaining satisfactory results.	- It uses only the local treatments and will not work when the patient and therapist are far from each other - Haptic sensation is not considered in this type of phobia.
VR Phobia Treatment System (e.g., acrophobia, claustrophobia,) [42], [43], [44].	- Developing a System for treating other types of phobias, such as acrophobia, Claustrophobia, fire, airplane, and public speaking.	- The delay requirement is not discussed since they approach local treatments - The haptic sensation and delivery of touch is not discussed in their proposed system
Haptic Smart Environment for Phobia [18].	- Developing a mobile augmented reality tool called PhobyTherapy application - Availability and accessibility of mobile technologies for small animal phobia treatme	- Instead of haptic gloves the TPAD Phones are used to provide tactile sensation when touching animals - There is no therapist in the process of treatment and patient her/himself selects the animals and scenarios based on the level of phobia - The system is not appropriate for the patients who has diagnosed with severe phobia
Remote Phobia Treatment [23]	- Cloud-based Remote Phobia Treatment System - Introduce a fog-based architecture for a remote VR phobia treatment application.	- Focused on the architecture and remote phobia treatment - Did not consider the probable message lost during remote phobia treatment - The availability requirement is not considered
- Prediction frameworks in the Tactile Internet era for Multiplayer VR interactive gaming. - Realtime Teleoperation [48].	- System architecture is proposed based on MEC and mmWave technologies for multiplayer VR interactive gaming in an indoor VR gaming arcade. - Players pose and actions can be predicted in the MEC network (prediction of force/torque samples in teleoperation systems).	- Did not present any further discussion on the reliability aspect of their work. - The proposed system satisfies the delay requirement of single/multiple-user VR applications (e.g., 20 ms). - does not cover the ultra-high reliability criterion.

a VR server. They can interact together via a shared haptic VR environment. Patient and therapist in this scenario have been equipped with VR headsets, haptic devices (e.g., haptic gloves), and tracking equipment for obtaining real-time visual, auditory, and haptic feedback. This equipment also could provide free movement in the VR environment.

To have a better understanding of a one-to-one remote therapy session, based on the authors' phycological papers, authors in paper [23] have considered the following main steps:

- First, the therapist establishes a connection and starts the session by providing initial instructions (i.e., verbal or textual).
- As the therapist and the patient both get ready and have access to the VR environment, the therapist adds a non-feared animal such as a butterfly to the virtual environment.
- When the patient feels comfortable with watching the butterfly, the therapist will gradually touch it. Haptic gloves and the remote phobia treatment architecture will enable both therapist and patient to feel the haptic feedback in real-time.
- The therapist then starts touching the feared object (i.e., spider) under therapist control, and both will feel the same sensation.
- Last steps for a successful treatment would be encouraging the phobic patient touching the feared object by herself.

The remote phobia treatment architecture in [23] has offered the required software modules. In addition, a prototype is implemented, and the delay measurements are performed in different use case scenarios. It is revealed that as the distance between therapist and patient increases, the end-to-end delay increases as well and the best measured achieved when all the architecture components are running locally. In their remote experiments, the therapist was based in Montreal, whereas the patients were located in three different cities. The measured average end-to-end delay were 52.33 ms, 78.18 ms, and 94.32 ms for Waterloo, Calgary and, Vancouver, respectively. Therefore, the mentioned paper does not meet the ultra low latency requirement discussed for the application (50 ms) when the patient and therapist are located in different cities. Moreover, the authors did not discuss about the ultra-high reliability requirement of Tactile Internet that needed to be addressed. The main advantages of approach presented in [23] is the haptic feedback delivery along with the audiovisual message transmission in the architecture. Moreover, measuring the end-to-end delay in different scenarios is another aspect of this paper [23]. However, the packet loss/delay issue and the method that may address this issue has not been discussed.

Fig 3.4: Phobia Treatment using Virtual Reality and Haptic Glove [23].

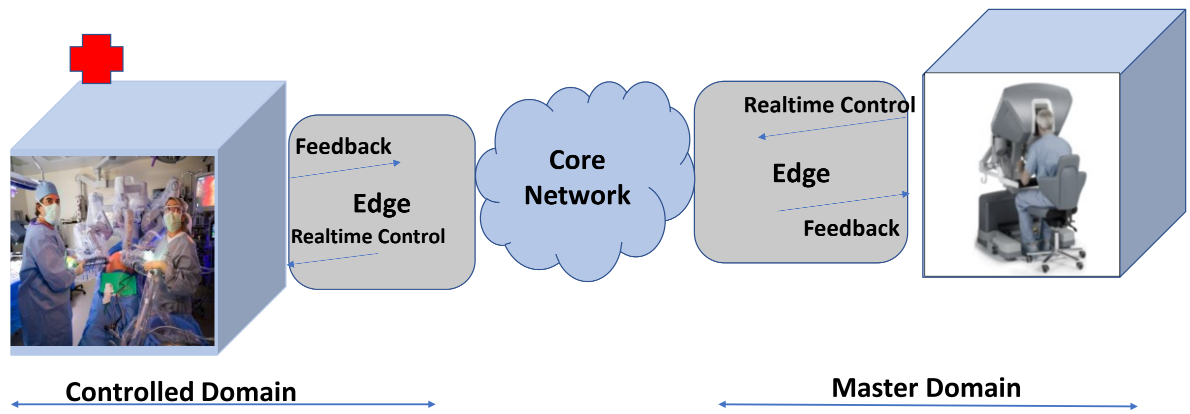

Figure 3.5: Remote Robotic Surgery.

3.3.2 Predicational Frameworks for the Tactile Internet

In the following, we focus on the papers, which focused on using machine learning approaches for Tactile Internet applications including in particular telehealth and phobia treatment. We mainly focus on machine learning methods for actions that can be carried out and can be mapped to phobia treatment (e.g., touching and grabbing a virtual object).

In the context of telehealth, there is a growing interest in using machine learning based prediction models for remote robotic surgery systems. The remote robotic surgery architecture as it is presented in reference [2] includes three main domains: (1) Master Domain, (2) Controlled Domain and (3) Network Domain. The master domain normally includes human and a master device for transforming human input to Tactile inputs. The haptic device in the remote robotic surgery context normally is used to govern the operations done by the controlled domain. The controlled domain consists of controlled robots which are directly governed by the master domain. The network domain is a medium for bilateral communication among master and controlled domain. The Tactile Internet let the human to communicate with the remote environment. Remote robotic surgery environment with the help of Tactile Internet allows the real-time interactions between surgeon and patient to touch, feel, and manipulate the objects in a physical and virtual environment. However, it necessitates ultra-reliable network connectivity which mandates scalability and low-latency for haptic interaction.

Machine learning gives the ability to the system to learn and perform actions without being programmed. For instance, [45] has used Gaussian mixture model/Gaussian mixture regression (GMM/GMR) to generalize set of forces and perform learning by demonstration. The predicted haptic feedback in [45] is suggested to be used when loss or delay happens in the network. The predictive model proposed in the paper [45] is based on the expert demonstration to enhance the safety and reliability in tele surgery. This work is among the limited works that has focused on the lost/delayed haptic feedback (i.e., force, torque, and position). In this paper the lost/delay in delivering the haptic feedback from patient to surgeon domain which will happen due to a poor network condition has been discussed.

In [46], the authors studied a fog-based action detection system by proposing an algorithm based on neural networks as well as a model for posture correction based on the analyzed behavior. Their proposed framework which is a Tactile Internet-based Ambient Assistance living (TILAA) in fog environment provides a reduced delay in collaboration between patients and doctors. The TILLA contains a microcontroller, sensing device and a battery holder. The chest wearable device includes actuators that are able to send Tactile feedbacks through vibrations to the doctors which are located in the hospitals. The proposed approach in [46] detects and corrects the back posture in a real time manner and allow doctors to monitor patient’s health during day to day activities such as exercise and medical diagnosis. Performance evaluation and a comparison between this method and previous expensive methods has revealed a superior performance for the back-posture correction for all the patients.

The authors of [47] proposed a heart disease prediction system using the *K*NN method. The main objective of this paper is to evaluate the effectiveness of considering fewer parameters for heart attack prediction compare to previous studies. They have used 8 parameters among the recommended 13 parameters (i.e., age, gender, chest pain, resting blood pressure systolic, resting blood pressure diastolic, resting ECG, resting heart rate, and Exercise induced angina). The experiment results for the 8 parameters using *K*NN presents an appropriate accuracy about 81.9%. In conclusion, the authors reached to the fact that the aforementioned 8 parameters are suitable enough to perform prediction for patients' heart attack. The remote treatment aspect and the end-to-end delay are not discussed in this paper and the authors mentioned about considering the machine to machine prediction system in the future.

The authors of [1] came up with a general introduction and focused on providing Tactile Internet in a 5G environment. They discussed on remote robotic surgery and autonomous driving as two main scenarios can be mentioned in remote scenarios. The remote robotic surgery scenario which is discussed in [1] relies on the edge architecture and referenced by several papers. Next, the authors elaborated on the Tactile Internet requirements related to latency and reliability, but they did not illustrate a detailed scenario.

In [48], the authors proposed an architecture based on multi-access edge computing (MEC) for multi-player VR interactive gaming in an indoor VR scenario. The results indicate that the proposed system performed satisfactorily regarding the delay requirement of single- and multiplayer scenarios. They also claimed that by enhancing the storage capacity of MEC network their proposed system can satisfy the delay requirement of 20 ms. However, they did not present any further discussion on the reliability aspect of their work.

In [4], after characterizing the Tactile Internet traffic, the authors relied on edge servers and proposed their so-called edge sample forecasting (ESF) module, which is responsible to perform multi-sample-ahead-of-time forecasting of the delayed and/or lost haptic samples in the feedback path of a bilateral teleoperation system by using multi-layer perceptron (MLP) artificial neural networks. However, did not discuss the delay and availability requirement in detail.

The authors of [49], have recently explored a new approach, to facilitate the remote environment simulation to mitigate the distance between master and slave by decoupling the limitation caused by perceived latency. Therefore, they have considered the latency requirement of human-to-machine communication (H2M). The AI-embedded cloudlet is proposed to predict the haptic feedback traversing from slave to master. To do so, as it is presented in Figure 3.6, they have obtained a VR based teleoperation setup within which the master (human operator) tries to touch a virtual ball with a pair of haptic gloves. A virtual ball is being touched in a VR environment and different haptic feedback will be sent to the human operator based on the material of the ball (metal, wood, plastic, or foam). Their proposed haptic feedback forecasting is through 2-phase AI (Artificial Intelligence) model. The first phase includes a series of Artificial Neural Network (ANN) which is implemented a supervised learning algorithm which performs based on binary classification correlated with touch detection (if touch is detected and if touch is not detected). In second phase, the Reinforcement Learning (RL) is applied to predict and deliver the haptic feedback to the master domain for assuring the quality of experience (QoE) which is required. Their proposed AI-based module is located close to the master domain which is able to forecast and facilitate the delivery of haptic feedback from slave to the master domain. The prediction approach will decouple the latency problem caused by the distance between master and slave domains. The prediction accuracy for the touch event and forecast feedback are reported 99% and 96% respectively that is very close to our recent work.

To the best of the authors' knowledge, none of the existing works aimed to decouple the impact of delayed and/or lost messages in a VR remote phobia system. Indeed, no work has considered the prediction of therapist's hand position or movement using predictive frameworks and machine learning techniques by focusing on edge computing.

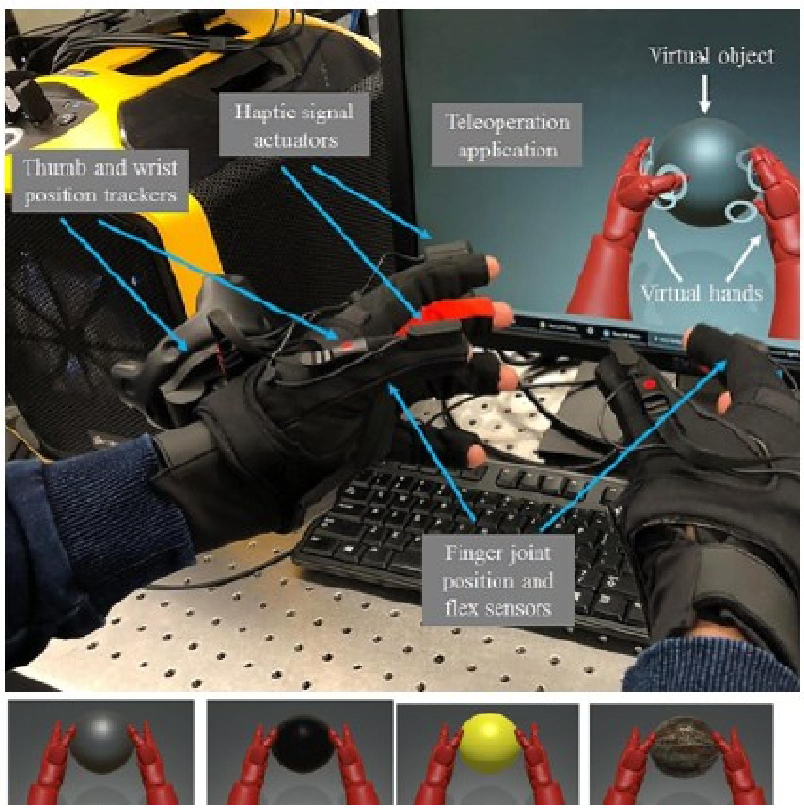

Figure 3.6: H2M Experiment between Master (2 VR gloves) and slave (virtual ball) with virtual ball of different materials: Metal, wood, plastic, foam [49].

3.4 Conclusions

In this chapter, we first presented the motivating scenario. Then we extracted a set of requirements based on the scenario presented. Afterwards, we reviewed and evaluated the related work. Table 3.1 provides a summary of the reviewed VR phobia treatment and machine learning correlated Tactile Internet papers. For each paper, we demonstrate the requirements which are met, or which are not met. Finally, we concluded that non-of the works presented in the state of the art met the considered requirements completely.

Chapter 4

Edge Tactile Learner

In this chapter, we first introduce the proposed predictive framework which is called Edge Tactile Learner by representing a scenario and a sequence diagram which mandate the need for designing a predictive mechanism. Afterwards, our proposed methods for solving the loss/delayed issue happening in the scenario will be discussed. It will be followed by introducing three weighting methods for the proposed method. In the last section, we review the proposed data generation process which is dedicated to phobia treatment use case.

4.1 General Overview of Edge Tactile Learner (ETL)

We propose our predictive edge tactile learner (ETL) particularly when an excessive delay or packet loss in the patient edge domain is recognized. When a time out is being activated, the edge tactile learner will receive the request for prediction the lost/haptic feedback.

To cope with the delayed and/or lost haptic messages (as discussed in Chapter 3), we design our predictive fog-based phobia treatment framework in the Tactile Internet era within which the therapist and patient are assumed to be in different fog domains. The delay/loss issue presented in Figure 4.1 mandates the need to design a mechanism to cope with the delayed/lost haptic feedback issue. Figure 4.1 illustrates a sequence diagram of a scenario in the process of remote phobia treatment within which the therapist and patient are located in different fog domains. In a typical situation, when the therapist attempts to touch a specific zone in the virtual reality coordinate system, once the zone detector receives the message from therapist tactile equipment (i.e., haptic glove), it does the mapping between the received spatial information and specified zone. Afterward, the information of the identified touched zone will be sent to the to the feedback generators of both therapist and patient sides. When both Feedback Generators located in different fog domains receive the zone spatial information, the corresponding haptic feedback will be generated, and the tactile devices will receive the haptic feedbacks generated by feedback generators. However, if the communication between the therapist and the patient experience delay/loss and the patient does not receive the associated haptic feedback within a required threshold (e.g., 50 ms), a negative impact especially in terms of user quality of experience will be imposed on the whole remote treatment procedure. Therefore, using the proposed predictive framework that can provide the accurate predicted haptic messages, both patient and therapist will experience a smoother treatment via Virtual Reality.

Towards this end, we propose our predictive edge tactile learner (ETL) to predict the haptic messages that could not reach to patient fog domain from therapist fog domain in time. At each time step, depending on the touched area, a zone is being transmitted from zone detector to both therapist and patient feedback generators. We note that “zone” refers to one of the many available 3D points, in the virtual reality coordinate system and at each time step, a zone will be transmitted from the zone detector to the patient and therapist correlated feedback generators.

4.2 Edge Tactile Learner

In the following sections, the two different variants of our proposed ETL, namely single-patient learner and multi-patient learner which is running at the edge of the patient's domain will be discussed.

4.2.1 Single-patient Learner

In the following, we develop a predictive framework to be run at the edge of the network. To begin with, we note that the classification algorithms are a group of supervised machine learning

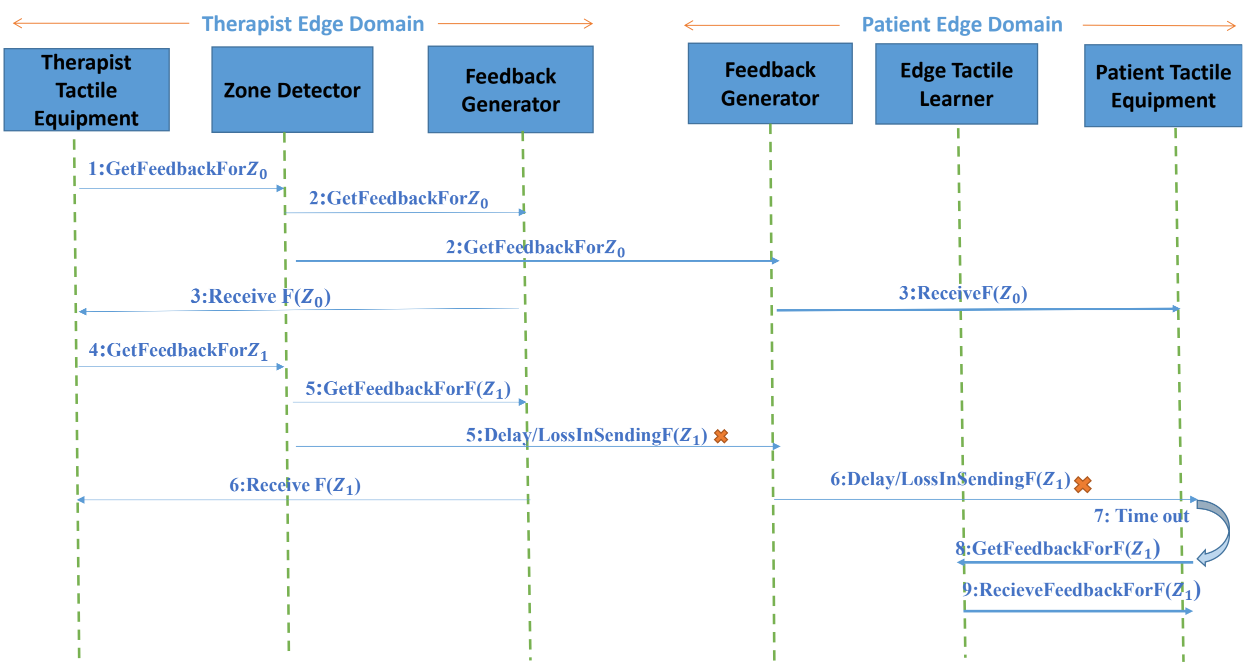

Figure 4.1: Predictive haptic feedback delivery during remote phobia treatment using our proposed ETL.

techniques that map an unknown input to one of the labels or classes from a finite set of data. There exist two main types of classification techniques: (i) binary classification, which classifies the tasks to no more than two classes and (ii) multiple class classification (also referred to as multinomial classification), which classifies the instances to one of more than two classes. This thesis focuses on multiple class classification. Our proposed ETL uses the well-known KNN method, which is known as a simple, yet immensely powerful tool for supervised data classification and prediction [17]. In KNN, new observations are classified into predefined classes based on a training dataset. The prediction will be done based on the nearest observations whose classes/labels are already known and observed. However, unlike the KNN which assigns identical weights to the observations, our proposed ETL take advantages of the weighting methods we have added to the KNN by simply considering different weights and priorities to the observations.

Let $Z = \{z_1, z_2, \dots z_l\}$ denote the set of l distinct zones. Let $\mathrm{z}_{\mathrm{t}}^{\mathrm{m}}$ denote a binary variable being equal to 1 when the therapist touches zone m at time slot t and zero otherwise:

$$z_t^m = \begin{cases} 1, & if\ therapist's\ hand\ is\ at\ zone\ m\ at\ t \\ 0, & Otherwise \end{cases} \tag{1}$$

Note that at each time step, the therapist can touch only one zone, which indicates that at each time step only one zone is active, and others will receive zero, thus:

$$\sum_{m=0}^{l} z_t^m = 1,\ \forall\ \ 0 \le t \le S\ ,\forall\ 0 \ll m \le l, \tag{2}$$

where, S is the length of the therapy session (given in milliseconds). The probability p^m of occurring zone m at a given time step is given by:

$$p^m = \frac{\sum_{t=c-k}^{c} w_t \times z_t^m}{\sum_{l=0}^{z_l} \sum_{t=c-k}^{c} w_t \times z_t^l} \qquad \forall \;\; l = 1 \ldots, l, \tag{3}$$

where c represents the current time step, k denotes the number of neighbors and w_t denotes the weight of each zone at time step t. The weights are assigned to the nearest neighbors using three weighing methods, which are explained in Section 4.3.

As the final step in our single-patient predictive framework, the output is calculated using the majority weight voting given by:

$$m^* \leftarrow \underset{m}{argmax}\, p^m \tag{4}$$

where m^* is the predicted zone by our single-patient learner at time slot t.

4.2.2 Multi-patient Learner

In the following, we turn our attention to multi-patient scenario and propose our *multi-patient learner*, which uses the information of multi-patient therapy session to perform accurate predictions. Typically, before the treatment begins, the therapist can measure the phobia level of the patients by having them fill a survey [3][4]. The patients can then be categorized into different groups based on their level of phobia. The level of phobia defines the therapy procedure. The multi-patient learner then predicts the next zone touched by the therapist at the prediction point (i.e., time step $c + n$) using the history of other patients in the same therapy session. To do so, our multi-patient learner repeats the four steps given by Eqs. (1) and (2).

Further, three weighting methods described in Section 4.3 are applied. The probability that the therapist touches zone m at the prediction point for other patient's same therapy session is calculated using Eq. (3) and the majority voting given by Eq. (4) is used to fulfill the prediction process.

In order to better describe the multi-patient learner functionality, let us assume that there are five patients with almost the same level of phobia under phobia treatment procedure. The patients are assigned into different groups based on their recognized level of phobia by the therapist. In the following example we have assumed that all five patients have finished their first session of their treatment. Afterwards, as it is shown in Figure 4.2 multiple patients will have therapy sessions. However, loss or delay may happen during transferring haptic feedback from therapist domain to the patient domain. Therefore, our proposed multi-patient learner would go through the other patient’s identical therapy session also the session that has experienced loss/delay if it is needed to

perform the prediction. We will go though the details of how multi-patient learner performs prediction by presenting two concrete scenarios which is illustrated by Figure 4.2 and Figure 4.3:

1) Let us consider an example that a loss/delay has happened at time step 10 for patient 3 regarding her/his second session of therapy. To elaborate more, assume there is a therapy session for patient 3. Therapist moves his/her hand in the virtual reality coordinate system toward the spider and other objects in the environment. However, at time step 10 for the patient 3, the haptic feedback related to the touched zone is not delivered from therapist to the patient. Therefore, as it is described earlier, time step 10 is called a prediction point. Consequently, as it is presented in Figure 4.2 and 4.3, for the sake of prediction and simplicity the data will be sorted out. The previous observations related to other patient’s therapy sessions will play an important role in forecasting the zone that has been touched by the therapist hand.

2) Second example illustrates a scenario related to the loss/delay which happens during the remote treatment for patient 5. It is worthful to mention that for patient 5, we have all other patients same therapy session available. Therefore, when the loss happens at prediction point (t=8), for k equal to 4, our proposed multi patient learner will use the previous observations related to patient 1,2,3 and 4 and even itself for predicting the lost zone touched by therapist.

4.2.3 Single-patient versus Multi-patient Lerner

There are some similarities and differences between our proposed single- and multi-patient learners. The main challenge for the single-patient learner is that it only relies on the obtained previous observations for the same patient. However, the multi-patient learner uses other patients' past observations and the same therapy session to perform prediction.

4.3 Weighting Methods

Recall that the KNN algorithm performs based on the k nearest neighbors of the training samples. For prediction purposes, it counts the number of samples, which belong to a specific label and assigns the label to the unknown data with respect to the majority voting. This, however, may neglect the fact that the samples closer to the unknown point may have higher impact on the decision outcome as compared to the samples located in further points. We therefore pay a particular attention to the weighted KNN (WKNN) to improve the classification performance of our KNN -based methods by proposing two different weighing methods for the learners described in the Sections 4.2.1 and 4.2.2. One of the key advantages of using WKNN is that the observations are treated nonequally, which may result in a better accuracy performance. The equal weighing

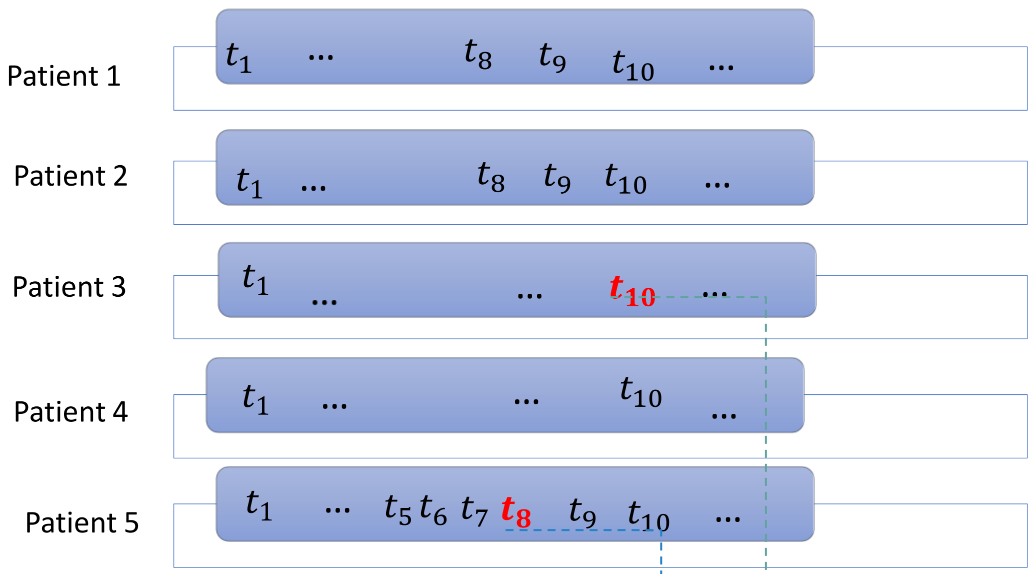

Figure 4.2: Therapy session 2 for five patients in the Multi-patient scenario.

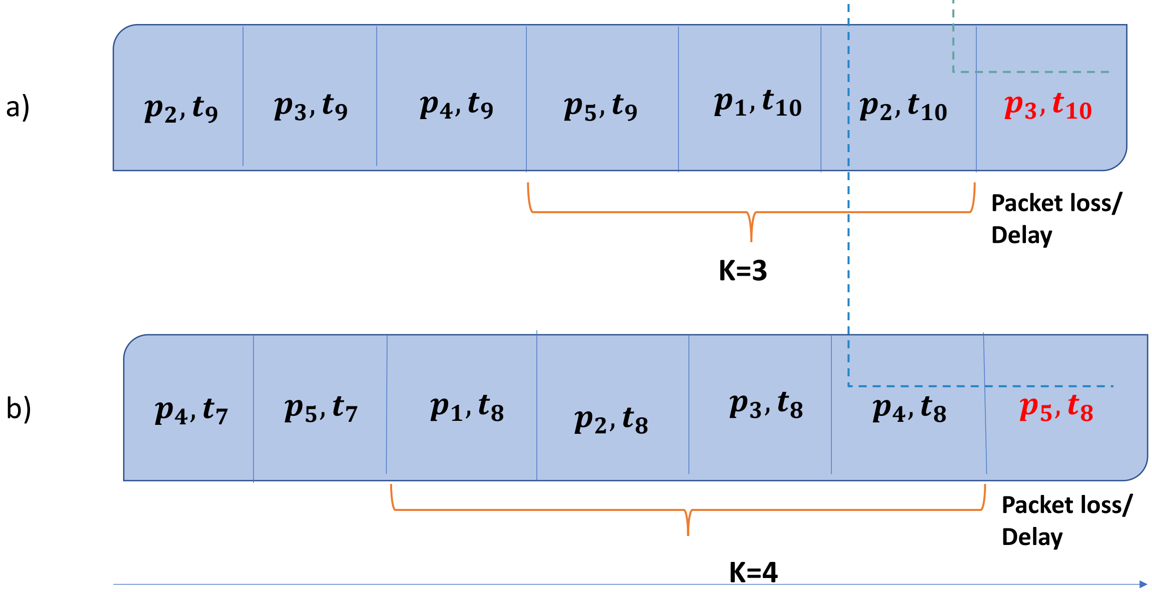

Figure 4.3: Multi-patient learner prediction procedure: a) when loss/delay happens for patient 3 during a therapy session at time step 10 and b) when there is a packet loss/delay during therapy session for patient 5 at time step 8.

method can be considered as normal KNN approach, which is used as the baseline for comparison with our proposed weighting methods.

1) **Equal Weight**: The equal weight method simply assigns identical weights to all the observations (i.e., $\mathrm{w_t} = 1 \ \forall \mathrm{t}$). It is assumed to achieve a lower accuracy compare to other weighting methods in forecasting. When considering the equal weighting method all the past observations are scored similarly and will be assigned equal weights.

2) **Temporal Weight:** In the temporal weighting method, the zone prediction probabilities are calculated based on the Euclidean distance between an unclassified observation and the training sample, as follows:

$$w_t = \frac{d_{t,c}}{\sum_{t=c-k\ldots c} d_{t,c}}, \qquad c - k \leq t \leq c \, . \tag{5}$$

where $d_{t,c}$ is the distance between the required observation at prediction point and the current observation. As a result, the nearest time step to the required observation point carries the highest weight.

$$d_{t,c} = \frac{d_{t,c}}{t-c+1} \ . \tag{6}$$

3) **Smooth Weight:** Our smooth weighing method assigns the weights based on the smooth trajectory of the zones touched by the therapist, which is in accordance with the semantic shape of the spider as well as the semantic distance from the other zones. In particular, we use the following smooth movement matrix:

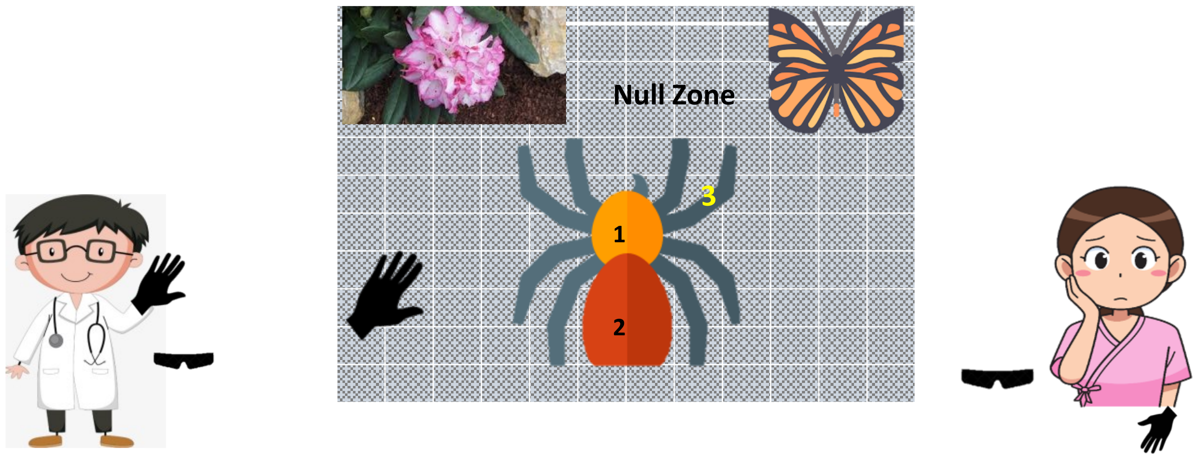

Figure 4.4: Simplified weight assignment in the VR coordinate system for the smooth weighting approach in a remote phobia treatment system where $\boldsymbol{Set\ of\ Zones} \leftarrow \boldsymbol{Z} = \{\boldsymbol{z_{1,} z_{2,} z_{3,} z_4}\}$.

$$M_{l\times l} = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 2 & \cdots & l-2 \\ 1 & 1 & 0 & 1 & \cdots & l-3 \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & 2 & 1 & 0 & \cdots & 1 \\ 1 & l-2 & l-3 & l-4 & \cdots & 0 \end{bmatrix}$$

where the semantic distance of each zone to itself is 0 and to the nearest neighbor zone is 1. The zone Null is assumed to have an equal distance of unity to all the other zones (see the first row in M). For the sake of argument as it is presented in Figure 4.4, let us assume there are four zones as: Null zone, head, body and leg, which is defined, i.e., $l = 4$ in the VR coordinate system. If the therapist touches zone 1 (i.e., head of the spider) at time step c, the weight of happening zone 3 (i.e., leg of the spider) at next time step is certainly lower than any other zones based on the semantic shape and distance. It is worthwhile to mention that it is not necessary to run a completely different pre-computing scheme for the smooth weighting approach when the type of animal is changed. The smooth weight w_t is then calculated as follows:

$$w_t = \frac{1/\widetilde{d_{t,c}}}{\sum_{t=c-k}^{c} 1/\widetilde{d_{t,c}}} \qquad \forall c-k \leq t \leq c, \tag{8}$$

where $\widetilde{d_{t,c}}$ is the smooth distance, which is given by:

$$d_{t,c} = \boldsymbol{M}.\left[\underset{m}{argmax}\, z_c^m\right]\left[\underset{m}{argmax}\, z_t^m\right] + 1. \tag{9}$$

Overall, we can conclude that our proposed temporal and smooth weighting approach will be expected to perform better in terms of accuracy. The reason for this argument is that the equal weighting method simply considers all the past observations equally in order to perform the forecasting. However, the smooth weighting gives more weight to the parts closer to the previously touched zones considering the animal (i.e., spider) body parts, and temporal weight is giving more weight to the zones that have just been touched in the last time steps. By considering the semantic shape of the feared animal or observing last touched parts (last occurring zones) in the virtual reality environment the chance of predicting the right zone will get higher.

4.4 Data Generation

Given that there is no available real-world dataset representing the zones touched by the therapist during VR-based phobia treatment, we decided to generate a dedicated dataset for our case study. Our data generation process is shown in Algorithm 1. Our data was generated using Gaussian noise and Roulette Wheel selection method [18]. The input for roulette wheel selection function is an array of probabilities or any positive number and the output would be an index of the selected one [18]. By using Roulette Wheel Selection, an imaginary dial is rolled as it is shown in Figure 4.4, It will then point to a random location along with a circle as there is a need to apply randomness in the process of data generation. The proportion of the circle that is taken up by each member of the population and therefor the likelihood of each class/zone to be selected is determined by that member's fitness. Moreover, the probability will be examined by fitness of individual divided by the total fitness of all the individuals which will reach us to probability of a class to be selected. It is worthful to mention that sum of the probabilities happening for all the classes is normalized to one and when using a roulette wheel selection, there is no need to implement a roulette wheel selector as a circle. Indeed, selection of a random number will be sufficient. Classes with a higher fitness proportion are less likely to be eliminated, However, there is still a chance for their elimination since their correlated probability is not equal to 1.

In Algorithm 1, μ and σ denote the mean and standard deviation of the Gaussian noise. Gaussian noise which is named after Carl Friedrich Gauss, is a type of statistical noise considering a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution [18]. We consider a smooth trajectory of zones touched by the therapist followed by the generation of next observation based on the smooth trajectory rule, which is defined by the smooth matrix defined by Eq. 6. During our data generation, we have added $\Delta = \frac{-\text{Noise}}{l-1}$ to all the zones except the zone which is positively receiving that noise (see line 9 in Algorithm 1). This is because when noise is added to one zone, that amount of noise should be deducted from all the other zones equally by considering the mathematics rule for having a balanced equation. For illustration, let us consider four zones A, B, C, and D in the VR coordinate system. Assume it is required that the probability of occurring zone A increases by, say, 10%. As such, the probability of the occurring zone A should be increased by 10%, whereas the probability of occurring each of the other zones (i.e., zones B, C, and D) should be deducted by 10%.

In our proposed data generation process, the null zone's occurrence compared to the other zones, in therapy session number one and ten differs. The null zone occurrence presents touching all the objects in the VR coordinate system except the feared object by therapist's hand in the VR system. The null zone promises to have lowest perceived feedback through the haptic glove. As it is presented in Figure 4.6, the therapist in the first sessions tries to get the patient comfortable with touching the feared object (i.e., spider). Therefore, the null zone's occurrence compared to other zones related to the feared object is much higher. However, session by session, the patient's fear toward the feared object will be reduced, and as it is presented in Figure 4.5, the patient will experience touching the feared object more often than the earlier sessions. Moreover, in Figure 4.6, which is related to the first session of phobia therapy, the differences between the happening of the null zone and other zones are greater than the identical difference in session 10 of phobia therapy. This is because the number of null zones happening in session ten has reduced substantially, and accordingly, the occurrence of other zones has been increased.

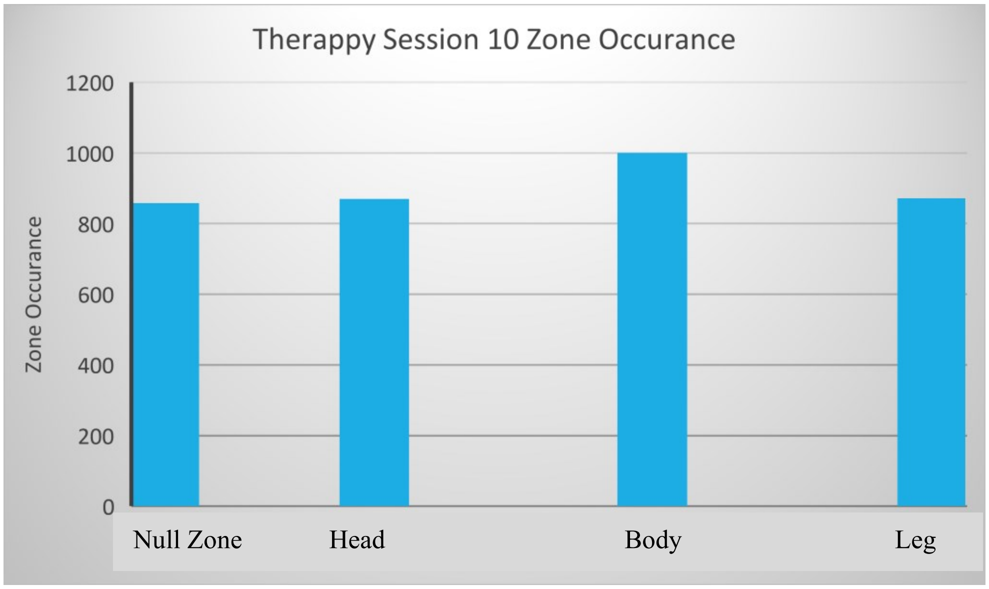

Figure 4.5: Occurrence of zones in therapy session number 10.

4.5 Conclusions

The problem of excessive packet latency as well as packet loss may result in quality-of-experience (QoE) degradation in VR remote phobia treatment system. Therefore, in this chapter a framework was proposed for predicting the haptic feedback which experiences loss/delay in the patient edge domain which can provide the zone detector of the patient with accurate predictions. The Feedback delivery during remote phobia treatment via our proposed ETL was described in detail through a sequence diagram. Afterwards, the proposed ETL which performs as single and multi-patient learner were described in detail in Section 4.1.2.1 and 4.1.2.2. In Section 4.1.2.3, we paid a particular attention to weighted KNN for improving the performance of learner's prediction by

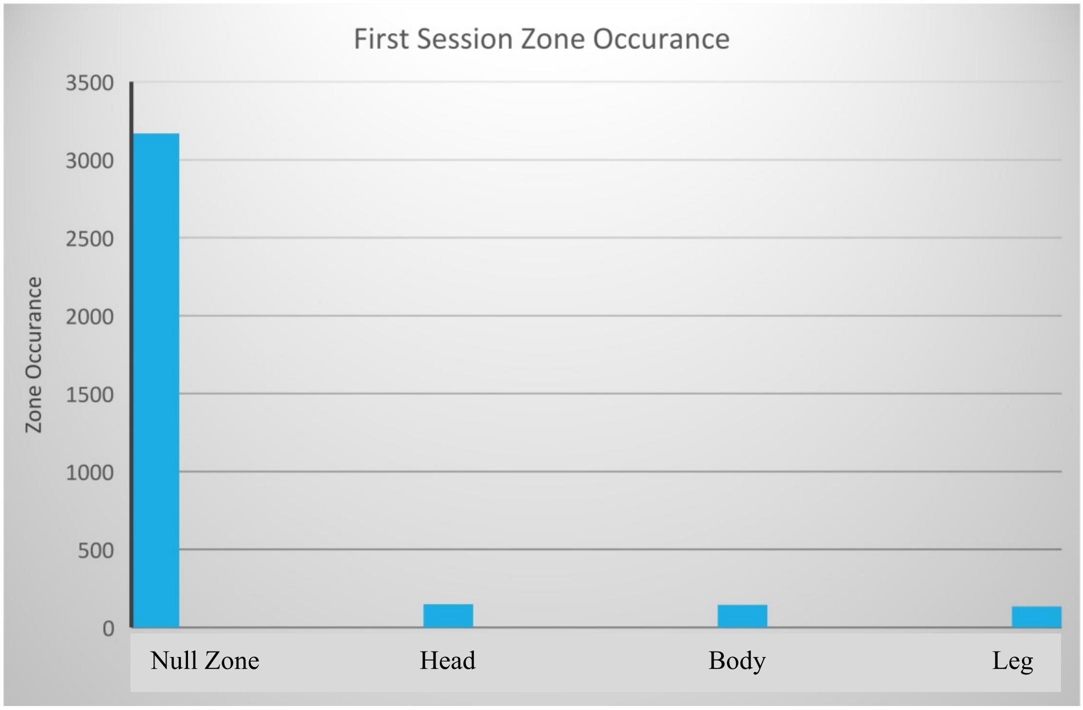

Figure 4.6: Occurrence of zones in the first therapy session.

Algorithm 1 Data Generation Procedure

Input: $initial\ noise\ mean\ \mu\ and$ noise standard deviation σ

1. $s \leftarrow$ Session Index
2. Set of Zones $\leftarrow Z = \{z_{1,}z_{2,} \dots z_l\}$
4. $current$ observation $\leftarrow z_1$
5. $t \leftarrow 1$
7. **while** $t < SessionLength$ **do**
8. $Noise \leftarrow N(\mu, \sigma)$
9. $P(z_t) \leftarrow Normalized\left(\frac{1}{(M[current\ observation][.]+1)}\right)$
10. $p_t^0 \leftarrow p_t^0 + Noise$
11. $\Delta = -\frac{Noise}{l-1}$
12. **for** $i = 1\ to\ l$ **do**
13. $p_t^i \leftarrow p_t^i + \Delta$
14. **end for**
15. Apply the roulette-wheel-selection on $p_t^m, \forall m = 0, \dots, l$ to obtain the new observation $z_t^m, \forall m = 1, \dots, l$ satisfying Eq. (2)
16. Current Observation $\leftarrow NextObservation$
17. $\mu \leftarrow \sigma - \beta$
18. t $\leftarrow t + 1$
19. **end while**

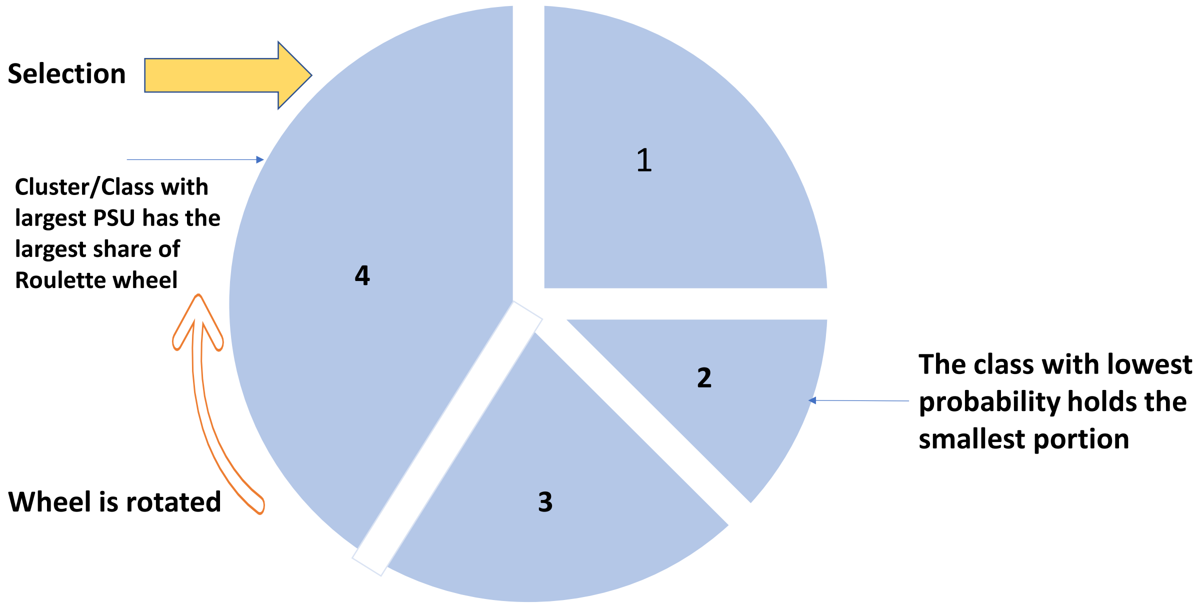

Figure 4.7: How Roulette Wheel Selection performs the selection process.

Chapter 5

Evaluation and Result

This chapter is dedicated to evaluating our proposed predictive framework. To this end, we experiment with the performance of our Edge Tactile Learner by considering the loss probability. We evaluated our proposed single patient learner and multi-patient learner by examining the accuracy of the prediction, followed by the time required for the prediction.

5.1 Simulation Setup

The simulation is done on Intel (R) Core i7-7700 CPU @3.6GHz. In our simulations, the impact of both delayed and lost samples is modelled by the so-called loss probability, which is defined as the probability for the packets that cannot meet a given deadline constraint. The loss probability also is defined by the probability that a transmitted sample is not delivered to the patient side in time. The loss probability is set to 30% as we assumed a poor network condition [50]. Moreover, it is important to note that the term "loss" in our performance evaluation refers to a packet drop, loss or delay of the packets that cannot meet a given deadline constraint.

We assume four zones in the VR coordinate system: namely, head, body, and leg of the virtual spider along with a null zone, i.e., $l = 4$. This can be justified in light of the fact that only a limited number of pre-defined vibration patterns can be generated by our considered remote phobia treatment system in [23].

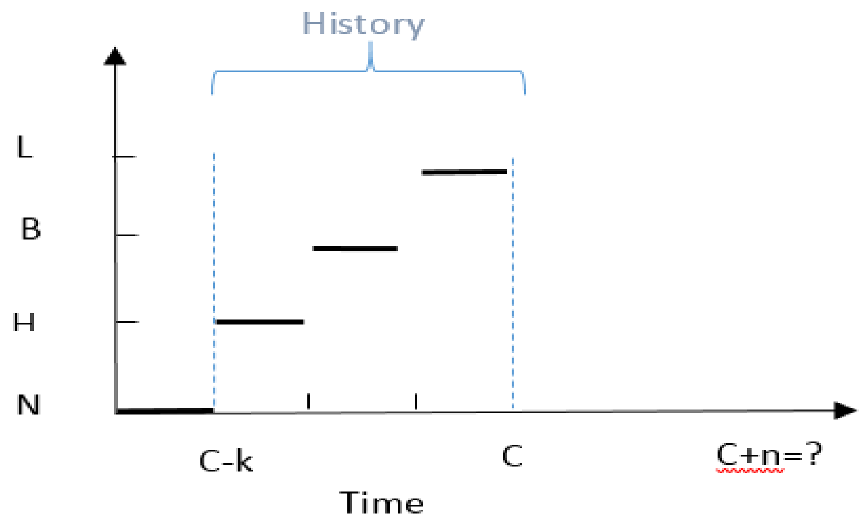

Figure 5.1: Prediction procedure at prediction point based on *k* previous observation.

We have considered the logistic regression and naive Bayes methods as benchmarks to compare with the performance of our proposed framework as these algorithms have widely been used in solving the multi-classification problems [39]. Specifically, the naive Bayes classifier is considered as one of the key multi-class classification approaches, where all the features are temporary and directly connected to classes with the so-called conditional freedom rule. Moreover, this method has an appropriate tolerance to missing values as well as short computational time in training. In contrast, logistic regression yields probabilistic outcomes of the observed data according to a given maximum likelihood argument [38].

5.2 Results for Single-Patient Learner

Fig. 5.1 presents the prediction scenario with the assumed four zones in the VR coordinate system, where the learner is able to predict the label at prediction point based on k previous observations (observation history). According to Figure 5.1, the loss/delay has happened at a prediction point presented by $c + n$. To predict the touched zone by the therapist at the prediction point, the history of the observed zones that occur from observation c to observations c-k is instrumental for the prediction purpose. The k will define the number of observations that should be considered for the prediction.

Figure 5.2 illustrates the accuracy vs. k-value for our proposed single-patient learner with the equal, temporal, and smooth weighting methods. According to Figure 5.2, it is evident that the temporal weight method has superior accuracy performance over the equal and smooth weighting methods. We observe in Figure 5.2 that the temporal weighting method achieves the highest prediction accuracy of 89.62% and 89.17% for k = 4 and k = 3, respectively. In contrast, the best-achieved accuracy for equal and smooth weighting methods are 82.47% and 70%, respectively, which are both obtained for k = 3. Also, note that the results of the prediction accuracy for logistic regression and Naive Bayes methods are shown in table 5.1, where their best-achieved performances were 62% and 61%, respectively. It is worth noting that, according to Figure 5.2, the accuracy performance of our proposed smooth weighting method stands somewhere between temporal and equal weighting methods. This is mainly due to the fact that the smooth weighting method uses a smarter assignment of weights compared to equal weighing by considering the semantic shape of the feared object. Therefore, the weighting process is much smarter than the

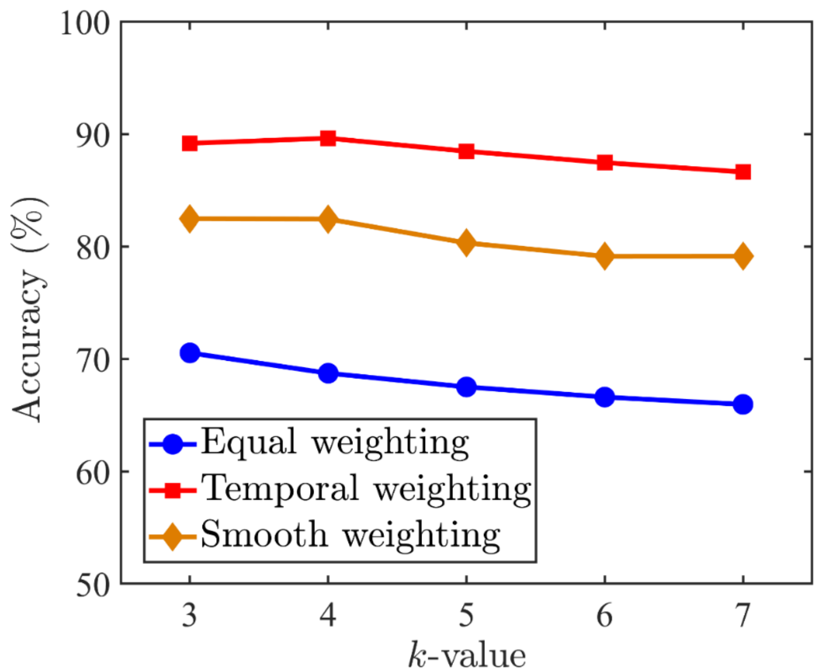

Figure 5.2: Accuracy vs. *k* for the single-patient learner with equal, temporal and smooth weighing methods (single-patient scenario).

equal weighting method, where the observations are considered equally. However, although the smooth weighting has a satisfactory result, but still could not compete with the temporal weighting method. Therefore, we can reach to the fact that considering the closer observations to the prediction point in terms of recent time steps, will bring more prediction accuracy than considering the semantic shape of the feared animal in VR coordinate system.

Figure 5.3 illustrates the prediction time vs. k-value for our proposed single-patient learner with equal, temporal, and smooth weighting methods. As shown in Figure 5.3, the equal weighting method runs faster than the other methods. This is not surprising since the equal weighting method considers the observations with identical weights, thus requiring fewer operations to perform a prediction. The shortest average prediction time for our single-patient learner with equal weighting method is 1.2 and 1.42 ms, which are achieved for k = 3 and k = 4, respectively. Our proposed

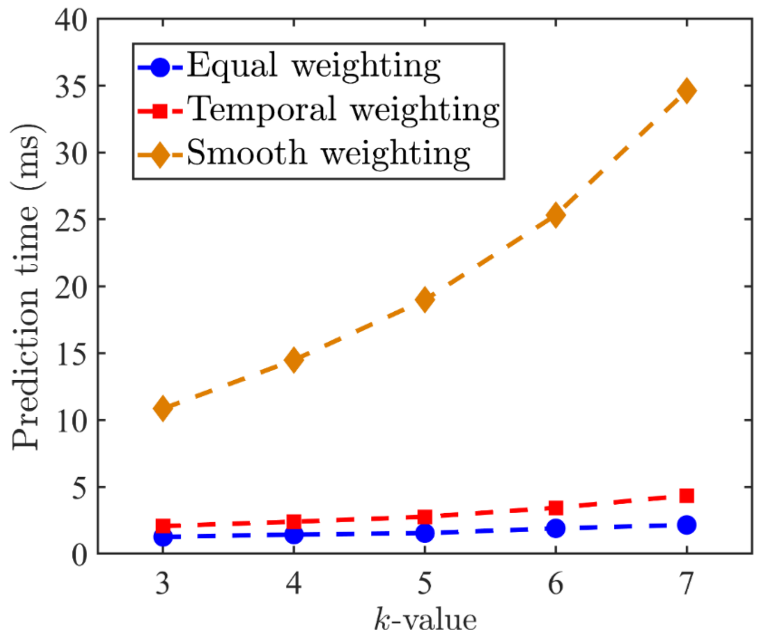

Figure 5.3: Prediction time (in ms) vs. k-value with equal, temporal, and smooth weighting methods for single-patient learner.

temporal weighting method not only can achieve the best accuracy performance compared to the other two weighting methods, but it can also achieve a prediction time close to that of the equal weighting method. On the other hand, we observe that the obtained accuracy of the equal weighting method is about 20% and 12% lower than those of the temporal and smooth weighting methods, respectively. This is mainly due to the fact that the equal weighting method is simply ignoring the importance of the weights that can be applied on the k nearest observations to enhance the accuracy of label selection and it applies equal weights to all the observation.

In addition, the shortest achievable prediction time of the smooth weighting method varies between 10 and 14 ms for k = 3 and k = 4, respectively. Due to its higher complexity, the smooth weighting method is subject to a longer running time than the equal and temporal weighting methods. The longest prediction time is associated with our proposed smooth weighting method, 34 ms for k = 7. This suggests that our proposed learners are all able to meet the 50 ms requirement of the haptic feedback transmission in a haptic-enabled VR-based remote phobia treatment system. It is worthwhile to note that the equal weighting method is associated with the shortest prediction time of 1.25 ms.

5.3 Results for Multi-Patient Learner

In the multi-patient scenario, we consider maximum five patients in each therapy session and ten sessions per patient. In both scenarios, the duration of the therapy is set to one hour [21]. The reason for considering maximum five patients for each session is regarding the existence of patients with different level of phobia therapy needed and the fact that every therapist in average has almost 25 to 45 patients each week. Thereby, approaching at most five patients which have specific level of phobia at a time would be feasible approach.

Next, we evaluate the performance of our multi-patient learner in terms of accuracy and prediction time. Figure 5.4 depicts the accuracy vs. k-value for the temporal, smooth, and equal weighting methods. We observe from Figure 5.4 that the temporal weighting method outperforms both equal and smooth weighting methods in terms of accuracy. To be more specific, the highest achieved accuracy under the influence of a 30% data loss rate in the network for the temporal weighting learner is 89.98%, while the accuracy value for smooth and equal weighting methods are 86.07% and 79.94%, respectively, which are achieved for k = 4. It is worth noting that the prediction accuracy of logistic regression and Naive Bayes were 58% and 60%, respectively, with the composition of training data and testing data by 70:30, thus being outperformed by our proposed methods.

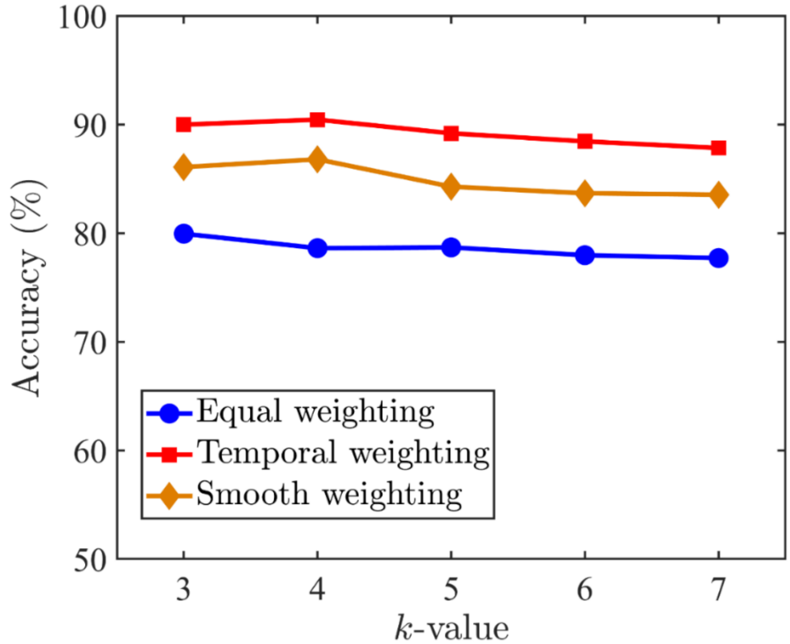

Figure 5.4: Accuracy vs. k for the multi-patient learner with equal, temporal and smooth weighing methods (multi-patient scenario).

Figure 5.5 shows the prediction time vs. k-value for the proposed multi-patient learner with temporal, smooth, and equal weighting methods. We observe that the prediction time of both temporal and equal weighting methods are close to each other. The equal weight method prediction time varies between 0.9 and 2 ms for k = 3 and k = 7, respectively. As for the temporal weighting method, the obtained prediction time is 1.7 and 4.4 ms for k = 3 and k = 7, respectively. The prediction time of the smooth weighting method is between 9.7 and 34 ms. This is due to the fact that the smooth weighting method has a higher complexity. Although the smooth weighting is

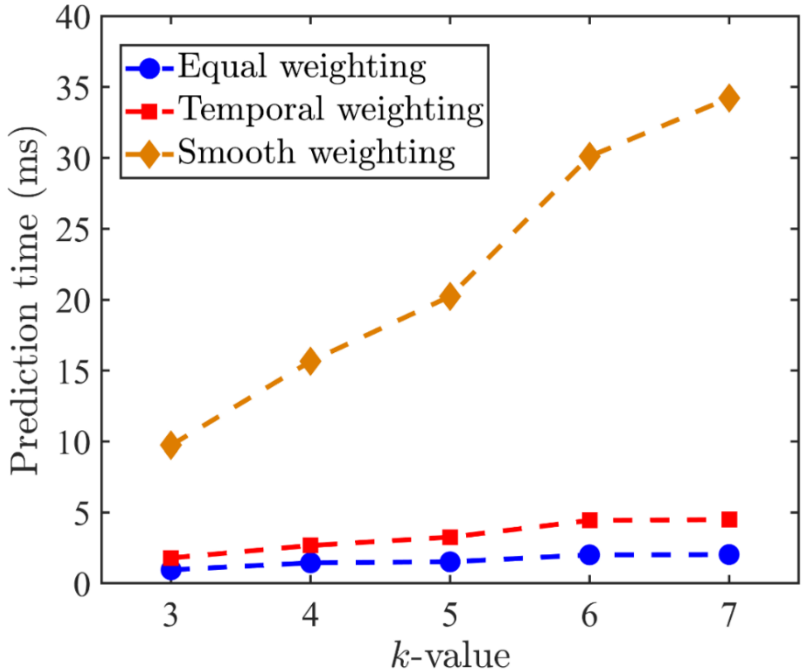

Figure 5.5: Prediction time (in ms) vs. k-value with equal, temporal, and smooth weighting methods for multi-patient learner.

associated with a longer prediction time, it still meets the 50 ms delay requirement and yet has an acceptable accuracy. For completeness, Table 5.1 summarizes the obtained results for the different proposed learning schemes along with the benchmark algorithms.

5.4 Conclusions

In this thesis, we studied the problem of excessive packet latency as well as packet loss in a VR-based remote phobia treatment system. The simulation results for the proposed learning-based predictive edge indicate that our proposed predictive framework outperforms the conventional Naive Bayes and logistic regression algorithms for both single and multi-patient scenarios. Specifically, our proposed multi-patient learner with temporal weighting method shows superior performance in terms of both accuracy and prediction time compared to equal and smooth weighting methods. Furthermore, the simulation results verify that our proposed single- and multi-patient predictive learners are instrumental in providing accurate predictions to the patient fog domain within the acceptable latency threshold, thus holding promise to increase the perception of immersion in haptic-enabled VR-based remote phobia treatment. The simulation results provided by the learners validated the designed predictive framework in the QoE evaluation by considering the requirements of low latency and high reliability in the Tactile Internet, we compare the performance of these three schemes from two different aspects.

Table 5.1: Summary of the accuracy and running time performance of different schemes.

Method	Accuracy	Prediction Time (ms)
Single-patient learner (equal weight, $k = 3$)	70%	1.25
Single-patient learner (temporal weight, $k = 3$)	89%	2.06
Single-patient learner (temporal weight, $k = 4$)	90%	2.3
Single-patient learner (smooth weight, $k = 3$)	83%	10
Multi-patient learner (equal weight, $k = 3$)	80%	0.9
Multi-patient learner (temporal weight, $k = 3$)	90%	1.7
Multi-patient learner (temporal weight, $k = 4$)	91%	2.6
Multi-patient learner (smooth weight, $k = 3$)	86%	9.7
Logistic regression	58%	1.27
Naïve Bayes	60%	3.99

Chapter 6

Conclusions

In this chapter, we will first summarize and highlight the contributions of the thesis and then outline some potential future works.

6.1 Summary of Contributions

Today's technological development would pave the path for the emergence of the so-called Tactile Internet. Tactile Internet is able to provide ultra-reliable and ultra-responsive network connectivity, which aims to transmit the real-time control and physical tactile experience remotely in addition to the conventional triple-play traffic (i.e., audio, video, and data). Haptic-enabled virtual reality is an interesting example of Tactile Internet applications, where low latency (less than 50 ms) is required. Tactile Internet is the key enabler of emerging applications such as Remote Phobia Treatment via virtual reality, which allows the patient to be treated by the therapist anywhere and anytime, regardless of their physical location. Remote Phobia Treatment, a greenfield in the telehealth domain, will let the remote therapists and patients touch and observe the virtual feared objects collaboratively by experiencing the real-time sensation of touch through a shared haptic VR environment. Not having to commute for the treatment procedure to see the therapist, not only stands time and cost-effective, but also brings tremendous benefits for both patients and therapists. As an example, Patients will be able to choose the desired therapist without having the distance concerns and therapist can have a wider range of patients compared to the traditional phobia treatment.

This thesis first provided a detailed overview of the background information related to Tactile Internet, Remote Phobia treatment, and relevant domains followed by the cloud and fog computing paradigm. Afterwards, we presented a Fog-Based architecture, along with description of the functional entities for remote phobia treatment. Then, we recognized the requirement of the described use case scenario for remote phobia treatment. The requirement we have identified fall into two main categories: Ultra Reliability and Ultra Low Latency. We also reviewed and categorized the most relevant related works into two categories: VR-based phobia treatment approaches and Predicational Frameworks for the Tactile Internet. Subsequently, we evaluated these related works based on the defined requirements.

It is worth noting that in this thesis, we focused on the recently proposed fog-based haptic-enabled VR system to treat the small animal phobia. The considered remote phobia treatment includes three broad domains; the therapist side fog domain, the patient side fog domain, and the core network domain. The core network domain is being used to facilitate communication between the first two mentioned domains. The therapist and patient communicate through a shared haptic virtual environment. However, even in the most reliable networks, certain haptic sensation messages might not reach in time to the patient fog domain.

To this end, a prediction framework is proposed to tackle the problem of packet loss as well as packet latency that may happen during remote phobia treatment procedure. Noting that the excessive end-to-end latency may lead to time lags between different modalities and might accordingly, to mis-synchronization, thus resulting in the so-called “cyber-sickens”. The cybersickness issue may cause quality of experience (QoE) degradation. Therefore, we have presented our proposed predictive framework as a single and multi-patient learner. The proposed predictive framework aims to use machine learning for decoupling the impact of latency/loss on user experience. The framework is built to predict the haptic messages experiencing loss/delay in a path traversing from fog therapist domain to the patient domain, followed by delivery to the patient domain. The proposed framework builds a model based on Weighted K-Nearest Neighbors (WKNN) by utilizing presented weighting methods to predict the zones touched by the therapist in a VR coordinate system associated with remote phobia treatment scenario. We also aimed to generate the dedicated dataset for the remote phobia treatment case study by considering the spider as the feared object. The data generation process considers the smooth movement of the therapist's hand toward the feared object in a VR environment.

Our evaluation and assessment results of the methods presented in Chapter 5 indicate that our proposed *Edge Tactile Learner* (ETL), is instrumental in providing accurate predictions to the patient fog domain within the acceptable latency threshold when a loss/delay happens for a haptic message traversing from therapist to patient fog domain. Thus, the proposed single- and multi-patient predictive learners are holding promise to increase the perception of immersion and QoE in haptic-enabled VR-based remote phobia treatment.

6.2 Future Research Direction

One future direction of this research can be considered as studying the current framework by examining security as another requirement of Tactile Internet applications, especially when the message loss happens. Dealing with the privacy issue can also be considered as one of the possible and interesting future research works.

Moreover, there is a possibility for validating the proposed method with a real dataset, mainly when the remote phobia treatment system works appropriately. To this end, there would be an opportunity to require an expert to simulate a therapy session for the patients remotely, and then gathering the real dataset would be a feasible approach. Considering the patients' reaction toward the feared object in the VR system is also an area for improvement in the proposed system.

As Edge Intelligence still is in its early stages, the Edge Intelligence/AI placement at the edge of the network, according to the scenario provided in the Remote Phobia Treatment, can be a feasible research approach.

Bibliography

[1] M. Simsek, A. Aijaz, M. Dohler, J. Sachs, and G. Fettweis, “5G-Enabled Tactile Internet,” *IEEE J. Sel. Areas Commun.*, vol. 34, no. 3, pp. 460–473, Mar. 2016.

[2] S. K. Sharma, I. Woungang, A. Anpalagan and S. Chatzinotas, "Toward Tactile Internet in Beyond 5G Era: Recent Advances, Current Issues, and Future Directions," in *IEEE Access*, vol. 8, pp. 56948-56991, 2020

[3] L. Atzori, A. Iera, and G. Morabito, “The Internet of Things: A survey,” *Comput. Netw.*, vol. 54, no. 15, pp. 2787–2805, Oct. 2010.

[4] M. Maier and A. Ebrahimzadeh, “Towards Immersive Tactile Internet experiences: Low-latency FiWi enhanced mobile networks with edge intelligence [Invited],” IEEE/OSA *J. Opt. Commun. Netw.*, vol. 11, no. 4, pp. B10–B25, Apr. 2019.

[5] A. Aijaz, M. Dohler, A. H. Aghvami, V. Friderikos, and M. Frodigh, “Realizing the Tactile Internet: Haptic Communications over Next Generation 5G Cellular Networks,” *IEEE Wirel. Commun.*, vol. 24, no. 2, pp. 82–89, Apr. 2017.

[6] S. Bouchard, S. Cote, J. St-Jacques, G. Robillard, and P. Renaud, “Effectiveness of Virtual Reality exposure in the treatment of arachnophobia using 3D games,” Technology and health care, 14, no. 1, pp. 19-27, 2006

[7] C. Mouradian, D. Naboulsi, S. Yangui, R. H. Glitho, M. J. Morrow, and P. A. Polakos, “A Comprehensive Survey on Fog Computing: State-of-the-Art and Research Challenges,” *IEEE Commun. Surv. Tutor.*, vol. 20, no. 1, pp. 416–464, 2018.

[8] “Edge computing vs. fog computing: Definitions and enterprise uses,” *Cisco*. [Online]. Available: https://www.cisco.com/c/en/us/solutions/enterprise-networks/edge-computing.html. [Accessed: 11-Nov-2019].

[9] Garcia-Palacios A, Hoffman H, Carlin A, Furness Iii TA, Botella C. Virtual reality in the treatment of spider phobia: a controlled study. Behaviour research and therapy. 1;40(9):983-93, Sep-2002.

[10] M. Chen, Y. Hao, K. Hwang, L. Wang, and L. Wang, “Disease Prediction by Machine Learning Over Big Data from Healthcare Communities,” *IEEE Access*, vol. 5, pp. 8869–8879, 2017.

[11] “Edge computing vs. fog computing: Definitions and enterprise uses,” *Cisco*. [Online]. Available: https://www.cisco.com/c/en/us/solutions/enterprise-networks/edge-computing.html. [Accessed: 11-Nov-2019].

[12] O. Simeone, ‘‘A very brief introduction to machine learning with applications to communication systems,’’ *IEEE Trans. Cogn. Commun. Netw.*, vol. 4, no. 4, pp. 648–664, Dec. 2018.

[13] R. S. Michalski, J. G. Carbonell, and T. M. Mitchell, Machine Learning: An Artificial Intelligence Approach. Berlin, Germany: Springer, 2013.

[14] D. Offord, Boyle. M, Campbell. D, Goering P, Lin. E, Wong. M, and Racine. Y "One-year prevalence of psychiatric disorder in Ontarians 15 to 64 years of age." *The Canadian Journal of Psychiatry* 41, no. 9 (1996): 559-564.

[15] M. Wrzesien, C. Botella, J. Bretón-López, E. del Río González, J.-M. Burkhardt, M. Alcañiz, and M. Á. Pérez-Ara, "Treating small animal phobias using a projective-augmented reality system: A single-case study," *Elsevier Computers in Human Behavior*, vol. 49, pp. 343–353, Aug. 2015.

[16] R. T. LeBeau, D. Glenn, B. Liao, H.-U. Wittchen, K. Beesdo-Baum, T. Ollendick, and M. G. Craske, "Specific phobia: a review of DSMIV specific phobia and preliminary recommendations for DSM-V," Depression and Anxiety, vol. 27, no. 2, pp. 148–167, Feb. 2010.

[17] I. A. Chicchi Giglioli, F. Pallavicini, E. Pedroli, S. Serino, and G. Riva, "Augmented reality: a brand-new challenge for the assessment and treatment of psychological disorders," Computational and mathematical methods in medicine, 2015.

[18] C. Ramírez-Fernández, A. L. Morán, E. García-Canseco, V. Meza-Kubo, E. Barreras, O. Valenzuela, and N. Hernández, "Haptic mobile augmented reality system for the treatment of phobia of small animals in teenagers," in Proc. *International Conference on Ubiquitous Computing and Ambient Intelligence*. Springer, Volume 7656, pp. 666–676, Berlin, Germany, 2017.

[19] T. D. Parsons and A. A. Rizzo, "Affective outcomes of virtual reality exposure therapy for anxiety and specific phobias: A meta-analysis," *Elsevier Journal of behavior therapy and experimental psychiatry*, vol. 39, no. 3, pp. 250–261, 2008.

[20] C. Paping, W.-P. Brinkman, and C. van der Mast, "An explorative study into tele-delivered multi-patient virtual reality exposure therapy system," Coping with posttraumatic stress disorder in returning troops: Wounds of War II, pp. 203–219, 2010.

[21] A. S. Carlin, H. G. Hoffman, and S. Weghorst, "Virtual reality and tactile augmentation in the treatment of spider phobia: a case report*," Elsevier Behaviour research and therapy*, vol. 35, no. 2, pp. 153–158, Feb. 1997.

[22] E. Steinbach, S. Hirche, M. Ernst, F. Brandi, R. Chaudhari, J. Kammerl, and I. Vittorias, "Haptic communications," *Proceedings of the IEEE*, vol. 100, no. 4, pp. 937–956, Apr. 2012.

[23] Y. Jebbar, F. Belqasmi, R. Glitho, and O. Alfandi, "A fog-based architecture for remote phobia treatment," in Proc. IEEE International Conference on Cloud Computing Technology and Science (CloudCom), Dec. 2019, pp. 271–278.

[24] O. Holland, E. Steinbach, R. V. Prasad, Q. Liu, Z. Dawy, A. Aijaz, N. Pappas, K. Chandra, V. S. Rao, S. Oteafy, M. Eid, M. Luden, A. Bhardwaj, X. Liu, J. Sachs, and J. Arajo, "The IEEE 1918.1 Tactile Internet standards working group and its standards," Proceedings of the IEEE, vol. 107, no. 2, pp. 256–279, Feb. 2019.

[25] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," *Computer networks, vol.* 54, pp. 2787-2805, 2010.

[26] C. E. Reiley, E. Plaku, and G. D. Hager, “Motion generation of robotic surgical tasks: Learning from expert demonstrations,” in 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, Aug 2010, pp. 967–970.

[27] M. S. Hossain, J. Bilbao, K. Abualsaud, K. Tourki and A. E. Saddik, "Enabling Networked Services and Technologies for Connected Healthcare," in *IEEE Network*, vol. 33, no. 6, pp. 6-7, Nov-Dec. 2019.

[28] Gianluca Noya, Farhan Khan, Gregor Tomic, Gerhard Fettweis, Norman Franchi, David Öhmann, Meryem Simsek, and Yaning Zou, Majed Al Amine, “Tactile Internet Enabled Pervasive Networks,” Accenture, 2018.

[29] R. Buyya, J. Broberg, and A. M. Goscinski, “Introduction to cloud computing”. Cloud *Computing: Principles and Paradigms*. John Wiley & Sons, New York. pp. 1-44, Feb 2011.

[30] L. M. Vaquero, L. Rodero-Merino, J. Caceres, and M. Lindner, “A break in the clouds: towards a cloud definition,” *SIGCOMM Comput Commun Rev*, vol. 39, no. 1, pp. 50–55, Dec. 2008

[31] Krishna Sharma S, Woungang I, Anpalagan A, Chatzinotas S. Towards Tactile Internet in Beyond 5G Era: Recent Advances, Current Issues and Future Directions. arXiv preprint arXiv:1908.07337. 2019 Jul.

[32] S. NIST, 800-145: The NIST definition of cloud computing 2012.”

[33]: I. Sriram and A. Khajeh-Hosseini, “Research Agenda in Cloud Technologies,” arXiv e-print 1001.3259, Jan. 2010.

[34] J. M. Evans, “HelpMate: an autonomous mobile robot courier for hospitals,” in *Proceedings of the IEEE/RSJ/GI International Conference on Intelligent Robots and Systems ’94. “Advanced Robotic Systems and the Real World”, IROS ’94*, 1994, vol. 3, pp. 1695–1700 vol.3.

[35] F. Bonomi, R. Milito, P. Natarajan, and J. Zhu, “Fog Computing: A Platform for Internet of Things and Analytics,” in *Big Data and Internet of Things: A Roadmap for Smart Environments*, N. Bessis and C. Dobre, Eds. Springer International Publishing, 2014, pp. 169–186.

[36]] M. Yannuzzi, R. Milito, R. Serral-Graciá, D. Montero, and M. Nemirovsky, “Key ingredients in an IoT recipe: Fog computing, cloud computing, and more fog computing,” *in Proc. IEEE 19th Int. Workshop Comput.-Aided Model. Design Commun. Links Netw. (CAMAD)*, Athens, Greece, 2014, pp. 325–329.

[37] S. B. Kotsiantis, ‘‘Supervised machine learning: A review of classification techniques,’’ Informatica, vol. 31, no. 1, pp. 249–268, 2007.

[38] P. Verlinde and G. Cholet, “Comparing decision fusion paradigms using k-NN based classifiers, decision trees and logistic regression in a multi-modal identity verification application,”

in *Proc. International Conference on Audio and Video-Based Biometric Person Authentication (AVBPA)*. Citeseer, 1999, pp. 188–193.

[39] M. Fatima, M. Pasha *et al.*, “Survey of machine learning algorithms for disease diagnostic,” *Journal of Intelligent Learning Systems and Applications*, vol. 9, no. 01, p. 1, 2017.

[40] D. V. D. Berg *et al.*, “Challenges in Haptic Communications Over the Tactile Internet,” *IEEE Access*, vol. 5, pp. 23502–23518, 2017.

[41] I. A. Chicchi Giglioli, F. Pallavicini, E. Pedroli, S. Serino, and G. Riva, “Augmented reality: a brand-new challenge for the assessment and treatment of psychological disorders,” *Computational and mathematical methods in medicine*, 2015.

[42] R. E. M. d. Oliveira and J. C. d. Oliveira, “Virtual reality system for the treatment of acrophobia,” in *Proc. IEEE Symposium on Virtual and Augmented Reality (SVR)*, Nov. 2017, pp. 74–77. MAIN 42

[43] D. P. Jang, J. H. Ku, Y. H. Choi, B. K. Wiederhold, S. W. Nam, I. Y. Kim, and S. I. Kim, “The development of virtual reality therapy (VRT) system for the treatment of acrophobia and therapeutic case,” *IEEE Transactions on Information Technology in Biomedicine*, vol. 6, no. 3, pp. 213–217, Sep. 2002.

[44] Juan MC, Alcaniz M, Monserrat C, Botella C, Baños RM, Guerrero B. Using augmented reality to treat phobias. IEEE computer graphics and applications. 2005 Nov 7;25(6):31-7.

[45] A. Chowriappa, R. Wirz, A. R. Ashammagari, and Y. W. Seo, “Prediction from expert demonstrations for safe tele-surgery,” *Springer International Journal of Automation and Computing*, vol. 10, no. 6, pp. 487–497, 2013.

[46] J. Vora, S. Kaneriya, S. Tanwar, S. Tyagi, N. Kumar, and M. Obaidat, “Tilaa: Tactile Internet-based ambient assistant living in fog environment,” Elsevier Future Generation Computer Systems, vol. 98, pp. 635– 649, 2019.

[47] I. K. A. Enriko, M. Suryanegara, and D. Gunawan, “Heart disease prediction system using k-nearest neighbor algorithm with simplified patient’s health parameters,” *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, vol. 8, no. 12, pp. 59–65, 2016.

[48] M. S. Elbamby, C. Perfecto, M. Bennis, and K. Doppler, “Towards Low-Latency and Ultra-Reliable Virtual Reeality,” *IEEE Network*, vol. 32, no. 2, pp. 78–84, March 2018.

[49] Wong E, Mondal S, Ruan L. “Alleviating the Master-Slave Distance Limitation in H2M Communications through Remote Environment Emulation”, In *2020 International Conference on Optical Network Design and Modeling (ONDM)*, 18 (pp. 1-3). IEEE, May 2020

[50] Boabang FG, R; Elbiaze, H; Belqami, F; Alfandi, O. A Framework for Predicting Haptic Feedback in Needle Insertion in 5G Remote Robotic Surgery. 2020 *IEEE 17th Annual Consumer Communications & Networking Conference (CCNC)*. 2020:1-6