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A Network-Adaptive Prediction Algorithm for Haptic Data Under Network Impairments

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ABSTRACT Real-time tele-haptic applications require capturing, compressing, transmitting, and displaying haptic information, which includes tactile and kinesthetic information. To achieve a high quality of service (QoS), real-time haptic data stream synchronization between local and remote environments is required. However, transmission of data over a computer network is often affected by network impairments, such as network delay, jitter, and packet loss, thus leading to system instability and poor performance. Current prediction algorithms for networked haptics comprise perceptual data reduction, traffic prioritization approaches, congestion control approaches, and radio resource allocation. However, the mentioned prediction algorithms either do not consider packet loss and time-varying delays (i.e., jitter) in their experimental setup, or only consider packet loss or delays. In real-world network environments, both packet loss and delays often occur simultaneously. In this work, a network adaptive Trust Strategy Prediction (TSP) algorithm was modified to work under both network impairments. The objective of the TSP is to maintain real-time haptic synchronization (haptic data stream synchronization) between the haptic interactive environments, by compensating network impairments using selective and specific prediction strategies, according to changes in the network's characteristics. The experimental results demonstrate that TSP offers greater accuracy and smaller inconsistencies in terms of the predicted position, compared to the dead reckoning prediction and velocity estimation, which is often employed with filtering techniques.

INDEX TERMS Communication network, haptic data prediction algorithm, tele-haptics, Trust Strategy Prediction.

I. INTRODUCTION

A key focus for current haptics research involves distributing haptic interactions remotely, which are defined as networked haptics (also known as tele-haptics). Tele-haptics [1], [2] is a technology that enables remote physical interactions with convincing touch experiences. It involves capturing, compressing, transmitting, and display of haptic information, including tactile (object identification or tactile dimensions), and kinesthetic (sensation of position/orientation) information. This information is transmitted over a computer net-

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work, between physically distant human beings, or between a local user and a remote location. Typical tele-haptic applications encompass medical [3], [4], simulation [5], [6], interactive gaming [7], and so forth.

Haptics require laws or policies to specify the action and reaction between forces (i.e., forces with Cartesian vectors) and motion (i.e., kinematics with Jacobian transpose) [9]. In an idealized transmission, the haptic data of both local and remote environments are updated and synchronized in real time. Unlike other types of network traffic such as text, graphics, audio, and video, which have met a relatively high quality of service (QoS) requirements, haptic transmissions have not reached such a high level of sophistication [2]. In many

situations, network impairments such as network delay and packet losses are unavoidable, which leads to lowered QoS, due to poor performance, unreliability, instability, and low fidelity during the haptic interaction. Delays can cause the remote operation to be ineffective, as real-time feedback is crucial. However, under certain circumstances, the delay time can be predicted from parameters which are independent of delay [10].

One approach to deal with the issue of real-time interactions which are affected by network impairments is to compensate it by using predictive algorithms [11]. Previous research studies in relation to the prediction of haptic data have resulted in significant improvement in the QoS, alongside the maximum compensation of network impairment effects (network delay and packet losses) [6], [12], [13], [14]. Haptic data generally consists of two interactive parameters, which are the position (including position/coordinate, velocity, acceleration, and orientation) and force (including resistance force, torque, and momentum). Positional data is used to exchange the state of the spatial location between the haptic environments, to determine movement, as well as to identify the collision contact points, where the force reactions occur. Without having regular and accurate positional updates, the presented force toward the user can become unrepresentative, and possibly unstable. This is the focus of our paper – positional data. A new network-adaptive Trust Strategy Prediction (TSP) is proposed to compensate for network impairments, by predicting the real-time haptic data. The TSP framework is adopted from our previous work [51], which predicted the velocity and yank estimations using positional data, based on historical haptic data and connectivity information. The results have been shown to produce better accuracy and less inconsistency, compared to the two well-known and popular positional prediction techniques used in networked haptics, which are the Dead Reckoning (DR) position estimation, and the Velocity Estimation with filtering (VE+F) technique [6], [7]. Both DR and VE+F techniques have been commonly applied in tele-haptics, for the aspect of maintaining hard real time, and upholding the consistency of the smoothness, respectively [15]–[19]. DR is seen as a fundamental technique, especially in predictive navigation, and has been frequently used in the haptic area when dealing with transmission delays and position estimation. The VE+F has been used to filter the noise when dealing with high sampling in haptic transmissions, to enhance the smoothness of the user experience.

The remainder of this paper is organized as follows: Section II reviews the related works, Section III discusses the proposed framework, Section IV describes the experimental platform and testing scenarios, Section V shows the outcome of the results, and finally, a conclusion is presented in Section VI.

II. RELATED WORK

A critical requirement in networked haptic interaction is to produce a natural and smooth gesture, body movement, and

a tactile or touch sensory feedback between the haptic environments, without the restriction of distance. Nevertheless, it is recognized that it is difficult to maintain a satisfactory user experience, whenever there are network impairments [13]. The researchers in [6], [7], [22] have carried out user experience quality surveys based on the mean opinion score tests, to evaluate the effect of haptic interaction under the influence of network impairments. Their evaluations have highlighted various network impairments, such as delays (including constant delay and variable delay), packet losses, low throughput, and background traffic interference. The performance and usability of the tele-haptic system in real-life scenarios are affected by network impairments, which include, but not limited to, network delays, jitters, and packet losses [20]. Different forms of network impairments affect DHVE interactions in different ways. For instance, the presence of network delays will result in the de-synchronization of the user's visual experience, and the complimentary haptic force feedback they receive within a virtual environment. In a non-jitter network, the data packet transmission is in a sequence interval, which will enable the receiving computer to process the data smoothly. A jitter network thus, will result in an inconsistent time delay and the receipt of an unsequenced data packet, down to the milliseconds(ms) during the transmission process. Jitters can create an unstable virtual environment (user experiences oscillating wave-like movements on the surface of virtual objects) [21].

A. HAPTIC TRAFFIC HANDLING APPROACHES UNDER DIFFERENT NETWORK ENVIRONMENTS

With the set of tight real-time constraints in haptic applications, many researchers have made significant efforts to minimize network impairments by applying the Quality of Service (QoS) methodology in order to prioritize haptic traffic over networks [11], [30]–[32]. Methods involving the application of traffic classification and prioritization mechanisms to the transmission of multi-modal data through a QoS-enabled IP network have yielded significant improvements in a user's haptic experiences, by minimizing network impairments [33], [34]. Marshall *et al.* [33] applied these mechanisms to manage haptic traffic congestion using the class-based weight fair queue (CBWFQ), as well as implementing the DiffServ's code point (QoS) mechanism. The utilization of the CBWFQ resulted in a significantly lowered end-to-end haptic delay, from 200 milliseconds to 40 milliseconds. Marshall *et al.* [35] applied the expedited forwarding, and assured that the forwarding classes treatments in a network employed the class-based weighted fair queuing in order to assign higher priority for the haptic traffic, thus, yielding a lower delay compared to other types of network traffic. However, this approach is applicable in managing prioritized networks, but not in non-guaranteed network channels, such as the general Internet.

For non-guaranteed network channels, Eid *et al.* [36] and Osman *et al.* [37] proposed an end node application layer-based data communication framework for multi-model

traffics (including haptic data) over a non-guaranteed/best effort network. They proposed multiplexing/multiple buffering to intelligently utilize the limited network throughput based on traffic prioritization policies. Their approach of adjusting the transmission rate according to the network impairments have shown significant improvement over data interleaving, but it could also lead to fluctuations in the haptic sequence intervals due to variations in the haptic update rate, consequently, causing a disrupted haptic experience. Cizmeci *et al.* [38] proposed a multiplexing scheme for multimodal tele-haptics. Bilateral tele-haptic occurs in a global control loop, that requires low-delay positions and force feedback exchanges to avoid small delays from jeopardizing the system's stability. Hence, it is important to prioritize transmission of haptic data. Their approach allocated resources to be shared amongst haptic, video, and audio, while prioritizing haptic signals over communication links with congestion and time-varying transmission rates. Gokhale *et al.* [39] proposed a lossless, network aware transport layer congestion control protocol, that adjusted the packet rate based on the congestion levels in the shared network.

Many have turned to "Tactile Internet", as a newly emerged form of the Internet, which is said to be "an ultra-responsive and ultra-reliable" network connectivity, which enables the transmission of physical haptic experiences remotely. The creation of the "Tactile Internet" aims to achieve a round-trip of 1ms, at an outage of approximately 1 ms per round trip (the expectation for reliable real-time haptic interaction) [22]. Due to this reason, the "Tactile Internet" highly relies on the fifth generation (5G) mobile network, which can support a round-trip latency of 1 ms (faster than 4G, which has a latency of 20 ms) [40]. To achieve ultra-low-delays, Condoluci *et al.* [41] developed a soft reservation strategy for uplink (UL) scheduling of the LTE-based networks for tele-haptic operations. The simulation results showed that the proposed strategy reduced the round-trip delay by an average of 10ms, compared with the legacy solution, which exploited the shorter Transmit Time Interval (TTI) proposed in [42], and envisioned in the 5G system. Aijaz [43] studied the haptic communication over 5G networks, specifically from a radio resource allocation perspective. They identified the key requirements of the radio resource allocation for haptic communications in the 5G-enabled human-in-the-loop mobile networks, which were a bounded delay, to ensure stable global control loop, a minimum rate allocation, joint, and symmetric resource allocation in the uplink and downlink. They formulated a power and resource block optimization problem which captured the QoS requirements, while accounting for specific constraints for the symmetric design case, which was the most dynamic haptic interaction scenario. They formulated a sum utility maximization problem under similar constraints for perceptual coding design cases. They proposed two different low-complexity greedy heuristic algorithms in both design cases to fulfill these requirements. The proposed algorithms had a polynomial-time complexity, and had also outperformed the

classical algorithms, in meeting the haptic communication requirements.

B. HAPTIC DATA PROCESSING USING REDUCTION APPROACHES

Yap and Marshall [22] investigated the QoS for DHVEs, by considering the force, visual, and textual traffic under network impairments conditions (packet delay, jitter, loss) over DiffServ networks. Their results showed that for optimal experiences, the DHVE network traffic needed to maintain a transmission rate of 1000 packets per second, with a maximum of 50ms delay, which was less than the 2ms packet delay variation (jitter), and less than the 10% packet loss. With such a high sampling frequency and transmission rate, the occurrence of the packet congestion and losses in the network increased. In order to enable a robust solution, Brandi *et al.* [23], [24] proposed a perceptual haptic data reduction scheme which kept the estimated impact below human perception thresholds. The authors used packet loss probabilities and round-trip time as parameters to predict unacceptable cases on the sender's side. However, their model assumed that the use of the time-invariant channel characteristics over time, which did not reflect the real-world packet-switched networks. In their next study, they improved the model by reducing the complexity of the binary tree, with a negligible increase in the packet payload. Hinterseer *et al.* [25] presented the first psychophysically motivated data reduction technique (Deadband principle), which transmitted data based on the previously transmitted data for haptic data streams. This approach reduced the packet rate without compromising the immersive depth of the system. The human perceptible force magnitude was set as the threshold for the data reduction algorithm. Bhardwaj *et al.* [26] investigated the human perceptible force using an adaptive sampling strategy to predict the haptic feedback based on human response time. In a closed loop system, every data reduction influences the system's stability. You and Sung [48] proposed the use of a floating-point haptic data compression to reduce the bandwidths used for haptic data transmissions. This compression mechanism was based on the concept that bit representations of consecutive floating-point numbers would change slightly from that of the most significant bit. In addition, an OR operation is then used to extract relevant bits from the floating-point numbers, and a prediction method is subsequently used to produce a smaller difference between the two consecutive floating-point numbers. This method allowed for transmission of haptic data, even in the presence of limited bandwidth. To guarantee the stability of the tele-haptic system, Hirche *et al.* [27] proposed a data reconstruction algorithm that included the passivity in dead-band control algorithms. However, they did not consider time-varying delays and packet losses in their experiment setup, and certainly did not impair the system's transparency. Xu *et al.* [28] combined the time domain passivity approach (TDPA) with that of the perceptual dead-band (PD)-based haptic data reduction

for the time-delayed tele-haptics, and proposed an energy prediction (EP) scheme. Their approach increased the data reduction, and improved the system transparency for the time-delayed tele-haptic communication. However, the energy predictor was less adaptive to the time-varying delay and the packet losses. Xu *et al.* [29] reviewed the model-mediated teleoperation (MMT) approach, which guaranteed both the stability and the transparency of the system, in the presence of communication delay. This approach had an efficiency which was highly dependent on the prior knowledge of the environment. With prior knowledge, the model's parameters can be estimated in real time. This approach rendered the feedback locally without delay, with accurate approximation of the remote environment. However, this approach cannot work efficiently in a complex environment.

Wongwirat and Ohara [44], Wongwirat [45] proposed an adaptive buffer approach to archive haptic media synchronization in a networked virtual tele-haptic interaction, which was affected by delay variations. They employed a moving average smooth filtering technique to calculate an average delay for the buffering adjustment. Their adaptive delay variation approach provided a smooth sequence of haptic update units. However, it sacrificed the real-time constraints (i.e., the greater the delay, the greater the adaptive buffering adjustment), and fast recovery from the data's inconsistencies (i.e., the greater the moving average of the smoothing filter's length, the slower was the response to the new data).

With regards to the concerns for the real-time smooth haptic update, Sakr and Georganas [6] proposed a predictive approach that relied on the least-squares and median filtering techniques in the haptic data reduction sphere. Islam *et al.* [12] proposed the use of a Lyapunov-Krasovskii-like function to solve the stability, in the presence of a variable communication delay. However, these approaches still had problems associated to the slow recovery from new data updates, and did not consider the other common network impairments, in particular packet losses.

C. HAPTIC DATA PROCESSING USING PREDICTIVE APPROACHES UNDER NETWORK IMPAIRMENTS

It is quite common to simultaneously encounter both network delays and packet losses in networks. Therefore, to achieve real-time haptic data synchronization, both jitters and packet losses must be compensated. Boukerche *et al.* [13] proposed a linear update predictive algorithm, which dealt with packet losses and delays. However, the prediction used was rudimentary and worked by estimating the position information inside the lost packet, through calculation of two historical information updates. This led to a huge positional discrepancy between the predicted and true positions, whenever burst losses occurred. Brandi and Steinbach [46] proposed the use of linear regression techniques to improve the prediction for the packet losses in the haptic communication. However, the experiment setting limits the coupling with the dead-band-based data reduction approach, and the low-complexity error-resilient data reduction scheme, to achieve improved

data reduction and decreased overall signal distortion. In [47], the authors proposed a hybrid sender- and receiver-based predictor to mitigate haptic artifacts caused by packet losses. This predictor was able to keep the signal distortion at the receiver to a minimum, without compromising the data rate reduction efficiency. However, this approach only considered the force and velocity parameter under the packet losses.

Boukerche *et al.*'s [14] approach focused on the use of two techniques - a decorator and algorithm, for which the decorator was controlled to moderate network delays in the haptic-based stimulated virtual environment. Firstly, a decorator (a visual cue embedded in the haptic virtual object) was used to inform the user regarding the current condition of the network delay. Subsequently, the complementary predictive algorithm was used to make linear predictions for the appropriate action. These two techniques work hand in hand to compensate network delays and lost packets, by providing the necessary calculations for the network delay/packet losses, as well as by improvising (predicting) its virtual displays based on its current state of network impairment. This approach provided the best quality results between remote users, when using a high loss network. However, it does not consider non-linear predictive algorithms which may produce better results than the current proposed linear predictions [14]. Zhou *et al.* [30] demonstrated the use of a concept based on the human arm trajectory characteristics to compensate for network delays in the case of haptic transmissions. Overshoot of forward prediction was inserted to cause instability in the haptic interaction. Therefore, similarly to the behavior of the human arm trajectory, the predictive algorithm proposed in this study seeks to lower the overshoot caused by the forward prediction. This approach overcomes the problems due to overshoot, as well as skips the step of buffering incoming data. Instead, it transmits predicted data instantaneously based on current network delays, which in return, improves the performance of the tele-haptic transmission. Although its effectiveness is clearly shown in terms of minimizing network delays, its implementation on the network jitter still requires further experimentation. Choi and Jung [49] proposed neural network-based tele-haptic using Smith Predictors to mitigate the jitter network. McCoy *et al.* [19] proposed an extension of the DR with neural network, termed neuro-reckoning, and Kusunose *et al.* [7] proposed an adaptive delta-causality control scheme with DR prediction to maintain the high interactivity. However, their DR relied on a single previous velocity value, to determine the predicted result that did not work well in the haptic environment, where the velocity was not always constant, and led to a surge in the peak position errors. In addition, use of neural networks require significant processing resources, and additional time to train the neural network in both local and remote environments, eventually leading to further processing delays.

On the other hand, our previous work [50] also concentrated on real-time tele-haptic control with an evaluation of the accuracy under the influence of network delays and packet losses, as well as different transmission rates. A positional

synchronization algorithm, called the Encoder Referencing Position Prediction (ERPP), was proposed to achieve better accuracy by compensating the network impairments, so that the sets of positional data between the two haptic peers could be synchronized in real time for haptic manipulation. The comparison results showed a significant improvement in terms of accuracy when dealing with constant delays and packet losses simultaneously, as compared to the DR. However, the results when dealing with jitters did not show much improvement. Therefore, the proposed framework presented in this paper aims to further enhance the real-time synchronization of the tele-haptic interaction in the presence of network impairments, such as jitters and packet losses, while maintaining the accuracy and consistency of the smooth haptic updates. We have adopted the quantitative evaluation technique of the haptic data prediction proposed in our previous work [51]. The proposed TSP framework can estimate the position data of the haptic data using the velocity and yank estimations. In this paper, we only focused on studying the position and velocity, because the force data was determined by the position or velocity.

III. PROPOSED FRAMEWORK

Due to network impairments caused by desynchronized haptic data streams between local and remote environments, it is a challenge for interactive environments to achieve realistic haptic interaction. As a result, operators experience low fidelity in haptic performances, such as coarse, irregular movement, and abrupt force reflection feedback. To minimize poor user experiences from the haptic data de-synchronization, the Trust Strategy Prediction (TSP) was proposed. TSP is based on the historical position and connectivity information, such as delay duration, and rate of packet loss, to predict the position in the current time. TSP has been subsequently used to compensate for network impairments, especially network delays (including jitter) and packet losses. Thus, it contributes to the stability and reality of the haptic interactions over non-guaranteed/best effort networks, like the Internet.

Fig. 1 shows the overview and flow of the proposed framework, consisting of three different stages; the haptic data handling and sorting, velocity acquisition, and prediction using the trust strategy. The operation of each stage is thoroughly explained in sections III.A, III.B, and III.C, respectively.

A. HAPTIC DATA HANDLING AND SORTING

The process of haptic data handling and sorting is meant to receive haptic data from the network, and keep it timely, even if it arrives out-of-sequence. Each time a new updated message is generated by the operator in the local environment, the remote environment listens to the incoming haptic data as well. Upon receipt of the haptic data, the remote environment software agent performs the necessary data sorting to ensure that the received data is in sequence, while maintaining the same timeline.

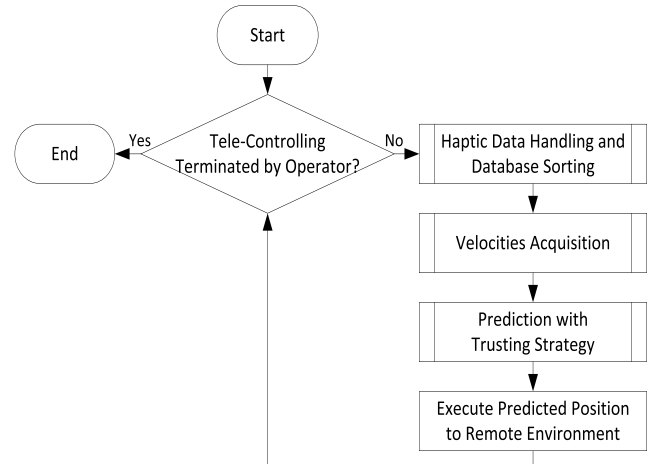


FIGURE 1. The haptic processing flow of the software agent in the remote environment.

In the remote environment, the received haptic data is stored in a database with arrays containing each set of data. For example, in dealing with the 6 degree-of-freedom positional data, the database will contain 6 arrays used to store the 6 axes of the positional data. Additionally, the size of arrays are dynamic, and based on the 5 most recent haptic packets (including any lost packets which are shown as null in the array). Each grid in the array is represented as 1ms timeslots. Every incoming haptic packet must perform time validation to keep the array synchronized in real time, and to discard any stale haptic packets. The time validation is performed by comparing between the time stamp of an incoming packet, and the time stamp of the most outdated haptic packet (known as the fifth packet) in the array. If the incoming packet's time is more recent than the fifth packet in the array, the fifth packet will be deleted from the array, and the incoming packet retained. Otherwise, the incoming packet is discarded.

Array rolling is required whenever new haptic data is saved. The purpose of this is to roll back the array based on the rolling gap to keep the timeliness. The value of the rolling gap is obtained from the received time interval ΔRT , between the time of last received packet RT_{t-1} and the time of the new received packet, RT_t , as shown in (1).

$$\Delta RT = RT_t - RT_{t-1} \quad (1)$$

Array rolling with the new data can only be saved into the particular grid of the array. As mentioned previously, the array grid is divided into 1ms timeslots, and the grid location which receives the data to be saved is based on the delay value D_t from (2).

$$D_t = RT_t - ST_t \quad (2)$$

where, ST_t is the packet issued time from the sender, which has been included in the packet as a time stamp. With these two equations, the array can only ensure the timeliness and sequencing, to provide an effective prediction. Fig. 2 illustrates a real test scenario, where the local environment sends

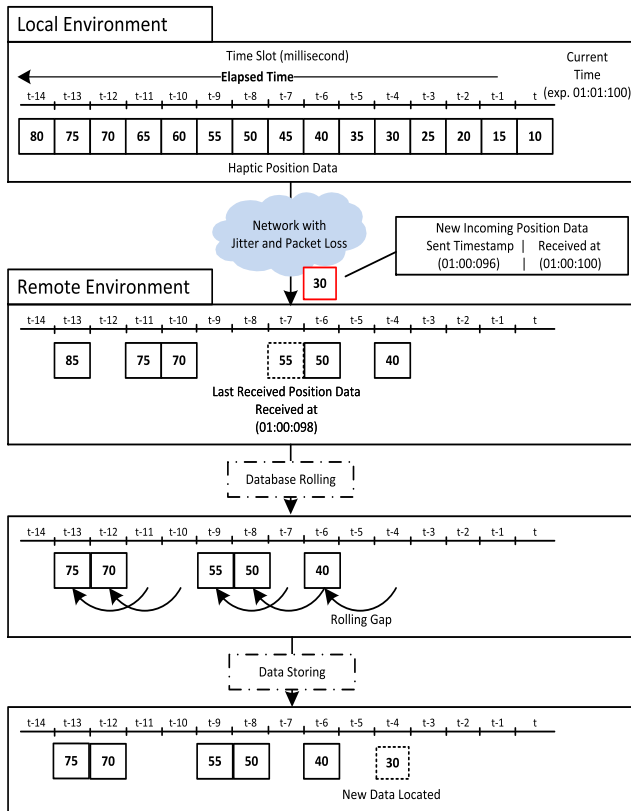


FIGURE 2. An example in detailed processing flow of haptic data handling and sorting.

the haptic position data to a remote environment over a network encountering jitters and packet losses.

The example in Fig. 2 shows that a haptic data with the position “30” was received by the remote environment at 01:00:100 (minutes:seconds:milliseconds), with its local timestamp 01:00:096. Before storing the received data in the array, the software agent has to ensure that the received data is in the same timeline as the last received data, otherwise it has to perform array rolling. The last received time in the example was 01:00:098, and the new received time was 01:00:100. Based on (1), the rolling gap between the two data arrival times was 2ms. So, the data in the array is required to roll back 2ms before storing the new received data into the right timeslot which was obtained from (2).

B. ACQUISITION OF VELOCITIES

After the array reaches the current timeline, the process of velocity acquisition is then entered. This helps to obtain the maximum three sets of velocity from the latest received position data, by using (3), the pseudo code for this, as shown in Fig. 3.

$$V_t = \frac{POS_t - POS_{t-1}}{ST_t - ST_{t-1}} \tag{3}$$

where, V_t is the estimated velocity between the new received position POS_t and previous received position

```

initialize last velocity to NULL
initialize new velocity to NULL
initialize first velocity to NULL
initialize second velocity to NULL
initialize third velocity to NULL
    
```

```

update first velocity as given in (3)
last velocity ← first velocity
while third velocity equal to NULL do
    POS_t ← POS_{t-1}
    ST_t ← ST_{t-1}
    Update new velocity as given in (3)
    if second velocity equal to NULL then
        second velocity ← new velocity
        last velocity ← second velocity
    else
        third velocity ← new velocity
    end if
end while
    
```

FIGURE 3. Pseudo code for obtaining three latest sets of velocity from the array.

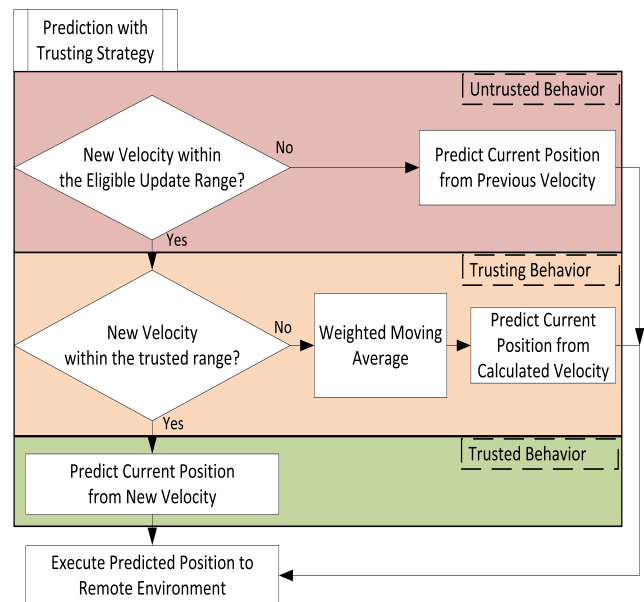


FIGURE 4. TSP algorithm consists of three behaviors for the inspection of incoming data.

POS_{t-1} , with the elapsed time duration between the new sent timestamp ST_t and previous sent timestamp ST_{t-1} . The pseudo-code ensures that the three latest velocities are acquired.

C. TRUST STRATEGY PREDICTION (TSP) MODELING

After the three velocity values have been acquired, the TSP is then executed to provide smooth movement and consistency of the haptic interaction, while maintaining the accuracy of the data prediction. The flow chart in Fig. 4 shows the overview of the TSP, and that it indicates each behavior produces a different predicted result, which relies on various network characteristics and haptic update patterns. Every incoming haptic data needs to go through this process and subsequently, the execution of the haptic update will be based on the predicted results from one behavior. TSP uses three

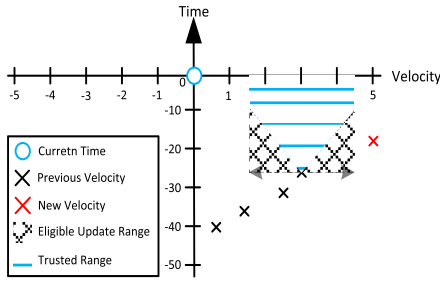


FIGURE 5. The scenario in untrusted behavior where the new velocity is out of the eligible update range.

predictive behaviors; untrusted, trusting, and trusted behavior. They are described in the following sections.

1) UNTRUSTED BEHAVIOR

The condition of the untrusted behavior is to prevent an abrupt motion from large velocity discrepancies, due to the latest incoming positional data. This phenomenon could possibly occur due to the burst packet losses, and a large gap between the variable delays (i.e., jitter), for example, whenever there is a wide range in the delay spread, or a low delay interspersed amongst the higher delays, which may trigger an abrupt motion. Therefore, the data with low delay needs to be held until it can be smoothly updated to the remote environment. As Fig. 5 illustrates, an eligible velocity update range is defined based on the last known valid velocity, known as the “previous velocity”, if the new velocity falls within the eligible update range. The eligible velocity update range (EUR) is shown in (4).

$$EUR = \begin{cases} EUR_{MIN} = \underline{V}_{t-1} - (\underline{V}_{t-1} \times C_{AP}) \\ EUR_{MAX} = \underline{V}_{t-1} + (\underline{V}_{t-1} \times C_{AP}) \end{cases} \quad (4)$$

where, EUR_{MAX} and EUR_{MIN} are the maximum and minimum values of the EUR, and \underline{V}_{t-1} is the previous velocity. C_{AP} is the arbitrary prediction constant, which is set to 0.05 for the best performance of the prediction under varying delays in the experiments. The value of C_{AP} was obtained using several trial and error runs, using the experimental platform. If the new velocity is out of the range and it is marked as untrusted, it means that an unexpectedly large inconsistency could have occurred when it is affected by the new received data. Hence, the latest received data is held and not used as a valid data, until it is within the EUR. Before that, the prediction is still based on the previous velocity values.

2) TRUSTING BEHAVIOR

After verifying the new velocity as that of an eligible velocity, the second behavior, which is the trusting behavior, is used to deal with the rough and inconsistent values that could be caused by the new velocity, which is out of the trusted range (TR). The TR velocity is shown in Fig. 6, and was obtained based on the two latest previous velocities, and the received

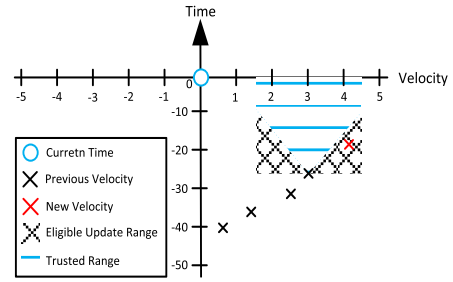


FIGURE 6. Trusting Behavior where the new velocity is within the eligible update range but out of the trusted range.

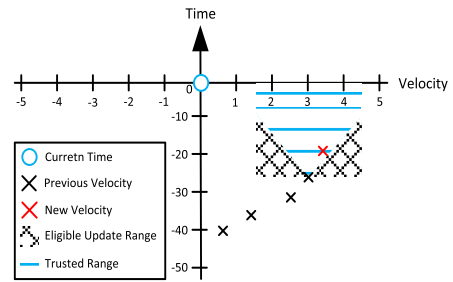


FIGURE 7. Trusted Behavior where the new velocity is within the trusted range and it is a valid velocity.

time of the new velocity. The formula is shown in (5).

$$TrustedRange = \begin{cases} TR_{MIN} = \underline{V}_{t-1} - \left(\underline{V}_{t-1} \times \frac{D_T}{100} \right) \\ TR_{MAX} = \underline{V}_{t-1} + \left(\underline{V}_{t-1} \times \frac{D_T}{100} \right) \end{cases} \quad (5)$$

where, TR_{MAX} and TR_{MIN} are the maximum and minimum limits of the trusted range. If the new velocity is out of the trusted range, a replacement of a new velocity which is based on a weighted moving smoothing average technique, is obtained from (6). The calculated result will be used as the current velocity to predict the current position, at the current time.

$$\underline{V}_{REPLACE} = \frac{\sum_{n=1}^3 \underline{V}_{n-3}(n)}{6} \quad (6)$$

where, $\underline{V}_{REPLACE}$ is the new velocity obtained by using a weighted moving average formula based on two previous velocities, and the new velocity. The denominator in (6) is the total weight applied in the velocities. The new velocity will be used as the current velocity, to update the current position of the remote object.

3) TRUSTED BEHAVIOR

In the last behavior of the TSP, the trusted behavior, it is meant as a go-ahead process to predict the current position based on the new velocity (without interference by untrusted and trusting behaviors), when the new velocity value is within the eligible updated range, where the trusted range is shown in Fig. 7. Therefore, the current velocity is same as the new velocity. With a valid current velocity, the current position can

then be predicted based on (7).

$$POS_P = \begin{cases} POS_{t-1} + \underline{V}_{t-1} (T - ST_{t-1}), & \text{if (UntrustedBhv.)} \\ POS_t + \underline{V}_{REPLACE} (T - ST_t), & \text{if (TrustingBhv.)} \\ POS_t + \underline{V}_t (T - ST_t), & \text{if (TrustedBhv.)} \end{cases} \quad (7)$$

where, T is the current time. After the current predicted position POS_P is obtained, the software agent in the remote environment will update and execute the predicted position toward the interacting object.

IV. EXPERIMENTAL PLATFORM

The objective of the experimental implementation is to study the effects of different levels of jitters and packet losses on the haptic control over the network. The combination of the packet losses, delays, and jitters are meant as network factors which are applied in the experimental platform, to simulate the real network phenomenon. These network impairments are generated in simulations, with no correlation between the samples, and thus leads to unpredictability. The experimental setup consists of two haptic environments, which are, local and remote. The local environment consists of a Phantom Omni haptic device [52], which serves as the motion controller and a local software agent, which runs on a Core i5 CPU, with 3.2GHz clock speed, and a 16GB DDR3 ram. Both the haptic device and the local software agent are interconnected with the IEEE 1394 FireWire cable. The remote environment consists of a custom-made 6 degree-of-freedom tele-robot assembled by aluminum frames, and with its joints attached by the HiTec servos [53], as well as remote-based software agents running on a Core i3 CPU, with a 3.4GHz clock speed, and a 4GB DDR3 ram. Both the tele-robot and remote software agent are interconnected with a universal serial bus connection link. Both environments are Internet Protocol (IP) networks, connected via a network emulator called the NetDisturb [54], which is used to emulate the network impairments in the traffic flowing between the two haptic environments. The network emulator runs on a Pentium 4 CPU with a 2.8GHz clock speed, and a 512MB SD ram. The software agents and network simulator are connected by a 1000BASE-T category 5e cable. The User Datagram Protocol (UDP) is used as the network's transmission protocol for the packet exchange, at a rate of 1000 packets/second. Fig. 8 shows the experimental setup used to perform the evaluation of the algorithm.

To compare the performances between the DR, VE+F and proposed TSP, the communication models and their associated parameters had been pre-defined to conduct the testing under the network impairments of variable delays (including different ranges of jitters) and packet losses. The NetDisturb applied a continuous uniform distribution [54] to generate the random jitter values, across three defined parameters; alpha (minimum additional delay in ms on top of constant delay), beta (maximum additional delay in ms on top of constant

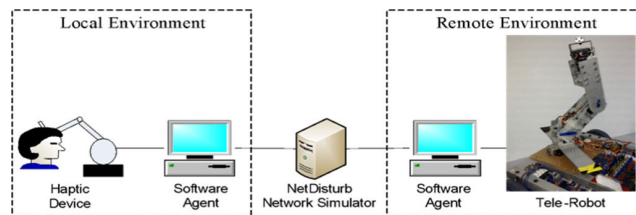


FIGURE 8. The overview of experimental setup.

delay), and constant delay. Table 1 shows the NetDisturb jitter settings used in the 20 sets of testing scenarios (TS) based on different packet loss rate settings, and variable delays. The TS was repeated 20 times, capturing at least 30347 packets every time. The jitter model was based on the addition of a delay to the selected packets. Packets without impairment were queued immediately. The percentage of the lost packets were configured according to the TS, with the burst losses ranging from 10% to 40%, out of 1000 packets/sec.

V. DISCUSSION OF THE RESULTS

In this evaluation, three important parameters, which were the maximum inconsistency, maximum, and average discrepancy from THE predicted result, were compared between the three predicted techniques, which were the DR, VE+F, and the proposed TSP, under the influence of different jitter settings and packet loss rates. The inconsistency was the absolute difference between the current predicted position, and last predicted position. This was used to verify the smoothness of the movement. The larger the inconsistency value, the less smooth the movement. The degree of discrepancy was the absolute difference between the predicted and real positions of the sources in the same timeline. This determined the accuracy of the prediction technique used. The joint angular degree ($^{\circ}$) from the Phantom Omni's x-axis (known as turret left+) was used as the measurement unit of the predicted response for this test bed.

All results are presented in the column charts, as shown in Fig. 9. The x-axis of the charts represents each prediction technique under the influence of each testing scenario, while the y-axis represents the position discrepancy, as stated by the unit of angular degree ($^{\circ}$). Since the average plots of the discrepancy is well below that of the maximum inconsistency and maximum discrepancy, it was connected for better visual representation. Fig. 9(a) and (b) show the comparative performances of the TSP, DR, and VE+F when operating under the influence of the network impairment, as defined in TS1 to TS4, and TS5 to TS8, respectively. Both figures represent the results under the influence of small levels of jitter, with different rates of packet losses (from 10% to 40%). Fig. 9(a) shows the predictive performance when affected by 20ms of jitter and Fig. 9(b) shows the performance when affected by 40ms jitter. In Fig. 9(a) and (b), the results show that TSP can maintain the average degree discrepancy below 0.15, with DR and VE+F being at 0.43 $^{\circ}$ and 0.16 $^{\circ}$, respectively. TSP maintained the maximum inconsistency and degree discrepancy



FIGURE 9. Comparison of Prediction Techniques with (a) up to 20ms variable delay with 10% packet loss in TS1, 20% in TS2, 30% in TS3, and 40% in TS4; (b) 10ms to 50ms variable delay with 10% packet loss in TS5, 20% in TS6, 30% in TS7, and 40% in TS8; (c) 20ms to 100ms variable delay with 10% packet loss in TS9, 20% in TS10, 30% in TS11, and 40% in TS12; (d) 30ms to 150ms variable delay with 10% packet loss in TS13, 20% in TS14, 30% in TS15, and 40% in TS16; (e) 40ms to 200ms variable delay with 10% packet loss in TS17, 20% in TS18, 30% in TS19, and 40% in TS20.

below 2.45° and 1.9°, while DR was up to 6.5° and 5°. VE+F was up to 3.2° and 2.7°, respectively.

The results shown in Fig. 9(c), (d), and (e) compared the relative predictive performance, when operating with the larger ranges of jitters, as well as packet losses. The test

scenario in Fig. 9(c) was under the influence of packet losses, and the 80ms jitter with 20ms minimum delay. The result illustrates that the TSP can keep the maximum inconsistency below 2.5°, while the DR and VE+F were up to 5.2° and 3.2°, respectively. In terms of accuracy, TSP maintained the

TABLE 1. Different attributes of variable delay with jitter settings and rate of packet loss in testing scenarios.

Jitter Settings			Variable Delay(ms)		Packet Loss (% out of 1000 packets/sec)			
Alpha	Beta	Constant Delay(ms)	Min	Max	10	20	30	40
0	20	0	0	20	TS1	TS2	TS3	TS4
0	40	10	10	50	TS5	TS6	TS7	TS8
0	80	20	20	100	TS9	TS10	TS11	TS12
0	120	30	30	150	TS13	TS14	TS15	TS16
0	160	40	40	200	TS17	TS18	TS19	TS20

average and maximum degree discrepancy below 0.47° and 4.17° , while DR was up to 0.97° and 8° . The VE+F was up to 0.5° and 5.3° , respectively. Fig. 9(d) was performed under a 120ms jitter, with a 30ms minimum delay, and the result indicated that the TSP can keep the maximum inconsistency below 4.5° , while the DR and VE+F were up to 6° and 5.7° , respectively. In terms of accuracy, the TSP maintained the average and maximum degree discrepancy below 0.77° and 4.3° , while the DR was up to 1.43° and 6.6° . The VE+F was up to 0.82° and 4.88° , respectively. Fig. 9(e) was performed under a 160ms jitter, with a 40ms minimum delay, and it was the largest frequency range among the testing scenarios. TSP was still able to maintain a maximum inconsistency below 6° , while the DR and VE+F were up to 12° . Moreover, TSP achieved a better accuracy of 1.26° on an average discrepancy. DR and VE+F were up to 2.17° and 1.34° . Fig. 9 also shows that the discrepancy was not proportional to the packet losses across all scenarios. The reason for this could be that the limiting factor for discrepancy was the variable delay and jitter, in contrast with the effects of packet losses which seemed to be insignificant.

VI. CONCLUSION

A new technique termed Trust Strategy Prediction was proposed to compensate haptic positional information used by tele-haptic applications, when operating under network impairments, especially for variable delay (jitters) and packet losses. The objective of the new technique is to achieve better accuracy, and minimize inconsistencies in terms of haptic synchronization, by considering the real-time constraints imposed by interactive haptics. The proposed algorithm adapts to changes in the interconnecting network, and responds to the incoming haptic data streams based on a trust strategy, with three behaviors; untrusted, trusting, and trusted behavior. The trust strategy conforms to the current trend of haptic interaction, and reacts to the appropriate behavior. With this approach, each behavior will react differently, and hence produce different predictions.

An experimental platform was used to compare the predictive performances of the TSP with other well-known haptic predictive techniques (DR and VE+F). The comparison platform used the accuracy of the haptic positional data for evaluating the predictive algorithms. The evaluation results showed that for every type of network impairment scenario examined, the proposed TSP produced a greater accuracy for the position prediction, while maintaining its consistency (smoothness of movement), as compared to the prediction

seemingly being based on conventional dead reckoning, and moving smoothing techniques.

This work focused on the haptic treating algorithm which will benefit subjective experiments. Future work, this will involve haptic user perceptions for the evaluation on tele-haptic manipulation, with the proposed TSP involving human subjective experiments. Moreover, with the current trend of Tactile Internet, an evaluation of the proposed TSP under wireless, or hybrid wired, is to be carried out. The behavior and stability of the TSP under communication impairments and data compression techniques will be included in future work. The future work will involve comparison of TSP performances with model-mediated tele-haptic techniques.

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