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MASTER THESIS

USER POSITION PREDICTION IN 6-DOF MIXED REALITY APPLICATIONS USING ARTIFICIAL RECURRENT NEURAL NETWORK

VORHERSAGE DER BENUTZERPOSITION IN 6-DOF-MIXED-REALITY-ANWENDUNGEN UNTER VERWENDUNG EINES KÜNSTLICHEN REKURRENTEN NEURONALEN NETZWERKS

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Statutory Declaration

I herewith formally declare that I have written the submitted master thesis independently. I did not use any outside support except for the quoted literature and other sources mentioned in the paper.

I clearly marked and separately listed all of the literature and all of the other sources which I employed when producing this academic work, either literally or in content.

I am aware that the violation of this regulation will lead to failure of the thesis.

29.06.2022.. Oleksandra Baga

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Listings

List of Abbreviations

ANN	Artificial Neural Networks
AR	Augmented Reality
CNN	Convolutional Neural Network
CPU	Central processing unit
DoF	Degree of freedome
DL	Deep Learning
FFN	Feed-forward Neural Network
GRU	Gated Recurrent Unit
HMD	Head-Mounted-Display
IEEE	Institute of Electrical and Electronics Engineers
KF	Kalman Filter
LAT	Look ahead time
LSTM	Long-Short-Term Memory
M2P	Motion-to-Photon
MAE	Mean Absolut Error
MEC	Mobile Edge Computing
ML	Machine Learning
MR	Mixed Reality
NLP	Natural Language Processing
ReLu	Rectified Linear Unit
RNN	Recurrent Neural Network
RTT)	Round-trip time
SDG	Stochastic Gradient Descent
VR	Virtual Reality
3-DoF	Three degree of freedom
6-DoF	Six degree of freedom

Introduction

1

This thesis is focusing on designing and evaluation of the approach for the prediction of human head position in a 6-dimensional degree of freedom (6-DoF) of Extended Reality (XR) applications for a given look-ahead time (LAT) in order to reduce the Motion-to-Photon (M2P) latency of the network and computational delays. At the beginning of the work the existing 3-DoF as well as 6-DoF methods were analyzed, and their similarities differences were taken into account when a proposed Recurrent Neural Network-based predictor was developed. The investigation of different neural network architectures and the improvement of head motion prediction is the main goal of this thesis. Proposed approach was evaluated and at the end of the work the obtained results were discussed and the suggestions for future work were done.

1.1 Problem statement

The correct and fast head movement prediction is a key to provide a smooth and comfortable user experience in VR environment during head-mounted display (HDM) usage. The recent improvements in computer graphics, connectivity and the computational power of mobile devices simplified the progress in Virtual Reality (VR) technology. The way users can interact with their devices changed dramatically. With new technologies of VR environment user becomes the main driving force in deciding which portion of media content is being displayed to them at any time of interaction with VR Applications [13]. Until recently the high-quality experiences with modern Augmented Reality (AR) and VR systems were not widely presented in home usage and were mainly used in research labs or commercial setups. The hardware for displaying the VR environment was once extremely expensive but recent years became more broadly accessible and the 6-DoF VR headset designed for the end-user were released[1]. It is possible now to experience virtual reality scenes and watch new type of volumetric media at home and the market interest for development VR and AR applications expected to be huge next years.
In fact, the existing on this moment virtual environments can be divided into two main groups depending on position of the user and their ability to move inside the VR environment. The user motion and prediction within a 3-DoF environment has been intensely researched for years. Extending such approaches to a 6-DoF

[1]https://medium.com/@DAQRI/motion-to-photon-latency-in-mobile-ar-and-vr-99f82c480926

environment is not straightforward, due to the change of the user's viewing point from inward to outward and additional three degrees of freedom [14].
Although all mentioned above improvements, rendering of volumetric content remains very demanding task for existing devices. Thus the improvement of a performance of existing methods, design and implementation of new approaches specially for the 6-DoF environment could be a promising research topic.

1.2 Motivation for the research

Research efforts to reduce the computational load are being already wide attempted. However, these approaches designed for the client side. Recently presented technique of the rendering on a cloud server makes possible to decrease the computational load on the client device by offloading of the task to a server infrastructure and than by sending the rendered 2D content instead of volumetric data [9]. The calculated 2D view must correspond the current position and orientation of a user. However, cloud-based streaming approach adds network latency and processing delays due uploading to a server the user position, rendering a new 2D picture from the 3D data and sending it back to a device. Thus, a rendered 2D image can appear even later on a display than with usage of local rendering system.
The promising research topic is reducing the Motion-to-Photon (M2P) latency by predicting the future user position and orientation for a look-ahead time (LAT) and sending the corresponding rendered view to a client. The LAT in this approach must be equal or larger to the M2P latency of the network including round-trip time (RTT) and time need for calculation and rendering of a future picture at remote server.

1.3 Structure of the thesis

The organization of this thesis is as follows. The thesis starts from introduction and problem statement, followed by theoretical background related to the research topic. Literature review chapter introduces different approaches and technologies of motion prediction algorithms. The chapters 4 and 5 show the implementation of presented model and evaluation of the results that were obtained during experiments. Last, the discussion regarding method limitations and suggestions for the future work are done.

Chapter 1 - Introduction.
The current chapter shortly introduces a state of development on scientific field achieved at a time of master thesis creation in the context on XR applications. The necessity of timely action to improve the situation with increasing computational

and network latency is shown in problem statement section 1.1. Due to the breadth of the research topic, the section 1.2 focuses the research topic and clearly motivates the implementation with neural network model.

Chapter 2 - Background.
The next chapter includes a review of the area being researched. It starts with a short introduction of the concept of MR applications and presents a 6-DoF environment. The presence and influence of a computational and network latency is covered, followed by discussion of possible solutions for its reduction. In section 2.5 the head pose estimation algorithms and the challenges faced in predicting of the viewer's position are discussed.

Chapter 3 - Related work.
The chapter provides an overview of previous research in the field of prediction of user's head position and orientation. The related works divided into section corresponding the computational approach of the prediction method. The chapter places a master thesis's topic in the context of the existing literature and the last section focuses in the methods using neural networks.

Chapter 4 - Data and Model.
Fourth chapter presents the design of the proposed method. The dataset including data collection from head mounted display (HDM) and data understanding and preprocessing are described in section 4.1, followed by a design of the algorithm including network architecture, functions of an input layers and the training methods.

Chapter 5 - Data and Model.
Fifth chapter gives an overview of the implementation of the described in previous chapter method. It describes the conducted experiments with a data obtained from HMD. The evaluation metrics and results are presented in the section 5.3.

Chapter 6 - Analysis.
The last chapter presents a discussion about the limitation of proposed method and provides a conclusion about the received results including suggestions for potential types of future research.

2 Background

This chapter introduces theoretical background of the presented research problem. First, the concept of mixed reality (MR) and the relation of this huge topic to the research field is presented, followed by an introduction of six degree of freedom (6-DoF) environment and the difference to the three degree of freedom (3-DoF). The term motion-to-photon latency (M2P) is covered, followed by a short discussion about an influence of M2P latency on the decreasing of user experience. The new developed cloud-based rendering and streaming approach is shortly discussed in this chapter. The last section of this chapter highlights challenges with the prediction of viewer's head pose that arises in modern XR applications in connection especially with the added network latency due the using of remote cloud server for computational offload.

2.1 Mixed reality

2.2 Six degrees of freedom

2.3 Motion-to-photon latency

2.4 Cloud-based volumetric video streaming

2.5 Challenges of head motion prediction

3 Related work

This chapter presents the overview of previous research in the field of the prediction of user position. It includes both approaches for 3-DoF and 6-DoF environment, focusing on time series methods, Kalman Filter and overview of Deep Learning Algorithms including methods using Recurrent Neuronal Network.

3.1 Time series methods

3.2 Kalman Filter

KF-based extrapolation are deemed to be robust against fast fluctuations, but suffer from susceptibility to noise sensory data [3].

3.3 Deep Learning Algorithms

Typical HMD computes user positions in 6-DoF by using its tracker module and data comes as time series with a sequential order. The structure of an input is crucial and needed to be followed in order to predict the next future step for a look-ahead time correctly. A sequence of inputs can be processed with Artificial Neural Network (ANN) called Recurrent Neural Network (RNN). Moreover, RNN can processes input with remembering its state while processing the next sequence of inputs. In the last decade, RNN algorithms have been adopted for motion prediction of 3D sequences. The authors *Aykut et al., 2018* claims their research to be first work that applies deep learning for head motion prediction. The current three rotations in three dimensions the so-called Euler angles as well as past values thereof within a certain time window (W) used as input for the network [3]. The best results delivered when 20 last values for each orientation direction (W = 250 ms) were used [3]. Instead of the absolute orientation values *Aykut et al., 2018* suggest for a goal of generalization for other datasets to subdivide the inputs into their respective orientation groups and compute their normalized differences [3]. The loss function MAE performed better compared to the MSE in experiments done by researchers. The authors experimentally confirmed that Feed-forward Neural Network (FFN) indeed had difficulties to learn for different delays even after an architecture was extended with the present delay and injected into all NN nodes. Next *Aykut et al., 2018* reasoned using of LSTM-based architectures with feedback loop and ability to establish a way of memory and share weights over time [3]. Researchers used Adam optimization algorithm, the maximum number of epochs was set to 1000, early stopping technique (patience = 2, min. delta = 0) was used to avoid overfitting. Additionally, the learning rate was decreased by 70% from initial value of 0.001 every 30 epochs. The batch size B was set to 2^{11}. Rectified Linear Unit (ReLU) as activation function for the FFN layers used with LSTM [3]. Three different architecture were tried. In all variants an input for NN was subdivided into dimensions and normalized within time window W set to 250 ms with $\triangle$t = 25 ms. Thus the $delay$ dimension of input vector is equal to 10. Final result obtained from each NN variant is a vector of length of 10 for each pan, tilt and roll dimension separately containing future prediction with LAT 1s and step of 0.1s.

First **interleaved LSTM+FFN** variant uses input of size $[D, delay, B]$ with D = [pan, tilt, roll] that goes into layer with nine nodes containing LSTM each. The output of this layer is fed together with initial input into nine nodes of FFN input layers. On second step an output of FNN with previously computed output from layer with LSTMs goes into new layer with nine nodes with LSTM in each node. Parallel to this the result of FNN separately goes into similar FNN again. This cooperation from LSTM and FNN loops calculations four times. The last loop's output from LSTM and FNN layers goes concatenated through layer with nine nodes with LSTMs once again and finally thirty-layered FNN produces a final output.

Second variant called **LSTM with subdivided inputs** in which each orientation dimension with input vector of size $[d, delay, B]$ with d containing one dimension goes through 10-layered stacked LSTM and the result of all three LSTMs forms new input vector of size $[D, delay, B]$ that is passed through 30-layered stacked LSTM. The output than goes through 30-layered FNN and thus final result for orientation with 1s LAT will be computed [3].

Third variant is **dense LSTM** with an input vector $[D, delay, B]$ that goes through input layer with 30 nodes containing LSTM each. Two additional intermediate layers with 30 LSTM nodes each perform computations and extract the features from the data. Final layer has 30 nodes of FNN and computes final result.

Conducted by researchers experiments showed that the LSTM-based architecture leads to a significant improvement of the MAE and RMSE metrics. The best performance is achieved by the interleaved architecture of LSTM and dense FFN blocks [3]. The LSTM-based methods were compared also to widely used approaches like the Linear Regression and a Kalman Filter based optimal state estimate. Thus *Aykut et al., 2018* demonstrated a substantial improvement of the deep predictor for latencies in the range of 0.1–0.9 s [3].

4 Data and Model

4.1 6-DoF Dataset

4.1.1 Data collection from HMD

4.1.2 Data Exploration

!! Data analysis AVG linear velocity position, plots

4.1.3 Data preprocessing

4.2 Neural Network

4.2.1 Network architecture

4.2.2 Network input

4.3 Training methods

Implementation and experiments 5

Here some code for my super neural network. The artificial neural networks discussed in this text are only remotely related to their biological counterparts. In this section we will briefly describe those characteristics of brain function that have inspired the development of artificial neural networks.

```
class StudentFactory(DjangoModelFactory):
        class Meta:
                model = Student
        student_card = factory.SubFactory(StudentCardFactory)
        first_name = factory.Faker('first_name')
        second_name = factory.Faker('last_name')
```

Listing 5.1: StudentFactory

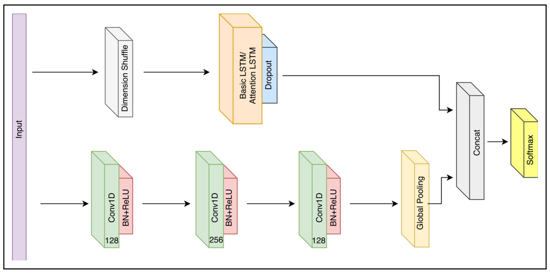

Figure 1: LSTM Fully Convolutional Networks for Time Series Classification

You might already know that you want to apply an established theory or set of theories to a specific context (for example, reading a literary text through the lens of critical race theory, or using social impact theory in a market research project).

5.1 Implementation

5.2 Experiments

5.3 Evaluation metrics

5.4 Results

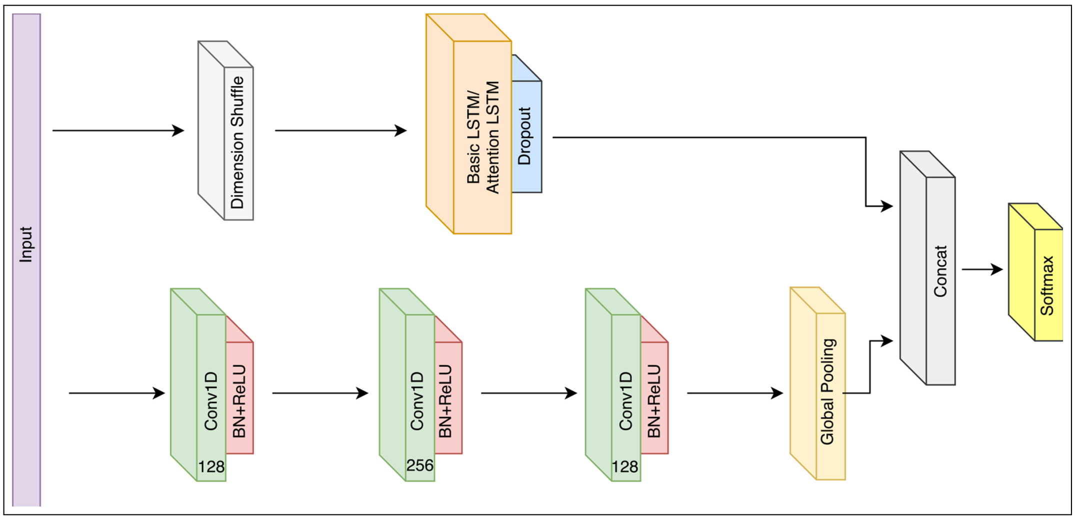

Figure 2: LSTM FCN WRAP

6 Analysis

The introduction text to analysis chapter

6.1 Limitations

6.2 Conclusion

6.3 Suggestions for future work

Glossary

AJAX

AJAX (asynchrones Javascript und XML) ist der allgemeine Name für Technologien, mit denen asynchrone Anforderungen (ohne erneutes Laden von Seiten) an den Server gestellt und Daten ausgetauscht werden können. Da die Client- und Serverteile der Webanwendung in verschiedenen Programmiersprachen geschrieben sind, müssen zum Austausch von Informationen die Datenstrukturen (z. B. Listen und Wörterbücher), in denen sie gespeichert sind, in das JSON-Format konvertiert werden.

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