Investigating the Effects of Eye-Tracking Interpolation Methods on Model Performance of LSTM

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ABSTRACT

Physiological sensing enables us to use advanced adaptive functionalities through physiological data (e.g., eye tracking) to change conditions. In this work, we investigate the impact of infilling methods on LSTM models' performance in handling missing eye tracking data, specifically during blinks and gaps in recording. We conducted experiments using recommended infilling techniques from previous work on an openly available eye tracking dataset and LSTM model structure. Our findings indicate that the infilling method significantly influences LSTM prediction accuracy. These results underscore the importance of standardized infilling approaches for enhancing the reliability and reproducibility of LSTM-based eye tracking applications on a larger scale. Future work should investigate the impact of these infilling methods in larger datasets to investigate generalizability.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

human computer interaction

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1 INTRODUCTION

Nowadays, eye tracking has emerged as an additional input channel for multi-modal interactions, as evidenced by studies such as [Esteves et al. 2015; Lischke et al. 2016; Turner et al. 2014]. However, optical and infrared eye tracking data are susceptible to data loss, particularly when the eye tracker encounters challenges in estimating pupil direction, frequently occurring during human blinks. This frequent data loss poses challenges for traditional methods of comprehending user behaviors and prediction models, including intent prediction, necessitating additional pre-processing steps. Consequently, various blink detection methods and strategies to address gaps in the input data stream have been explored. Grootjen et al. [2023] underscored the absence of standardized processes to overcome challenges posed by eye blinks, introducing a significant impediment to the reproducibility and comparability of findings across diverse studies. Following this, Grootjen et al. [2024] showed the inconsistencies in reporting and the influence different use-case-specific approaches have on the internal validity of eye-tracking studies. While some interactive systems disregard input affected by missing data, this practice introduces input lag and unexpected jumps and jitters, substantially diminishing system usability [Lugrin et al. 2013; MacKenzie and Ware 1993]. As machine learning methods, such as recurrent neural networks (RNN) and long short-term memory (LSTM), gain popularity for processing and predicting interactions, their effectiveness is contingent on a consistent data input stream without gaps. Consequently, the current understanding of the impact of the different infilling methods on the quality of these LSTM and RNN models.

Diverse interactive systems leverage eye tracking to enhance functionality, encompassing applications like direct manipulation [Lischke et al. 2016; Pfeuffer and Gellersen 2016], action prediction [Zhang et al. 2022], and gestures [Drewes and Schmidt 2007; Zhang et al. 2017]. Recent advancements have seen these systems incorporating neural networks to refine traditional feature extraction methods, as demonstrated by studies such as [Aftab et al. 2020; Zhang et al. 2022]. However, the inherent challenge lies in the neural networks' limited capacity to handle missing information during blinks effectively. Consequently, prevalent strategies for dealing with data loss from eye trackers involve either excluding data with blinks, as observed in [Ekman et al. 2008; Gunawardena et al. 2019; Wang et al. 2021], or attempting to fill in the missing information, as explored by Stein et al. [2022], utilizing use-case-specific and device-specific approaches. Regrettably, these studies often neglect concerns of reproducibility and generalizability, omitting evaluations of the impact of fine-tuning, such as specific parameters for infilling methods. Moreover, blinks introduce artifacts into the retained eye tracking data, and despite their acknowledged presence in the literature [Abel et al. 1983; Collewijn et al. 1985; Epelboim and Suppes 2001], present-day systems frequently overlook addressing these artifacts, leading to a general tendency to ignore the affected input. Consequently, there is an imperative need to establish a comprehensive and consistent pre-processing approach for eye tracking data to ensure the reliability and validity of interactive systems utilizing eye tracking.

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Evaluating the impact of these different infilling methods on openly available datasets will bring an understanding of potential generalization issues and will allow us to formalize recommendations to overcome them. Therefore, future work will know which of these infilling methods to apply without interfering with the output of their machine learning models. Thus, we have used the recommended infilling methods from Grootjen et al. [2024] on an openly available dataset from Annerer-Walcher et al. [2021]. By using their data and model structure, we can observe the impact of the different infilling methods on the accuracy of the LSTM model.

In this work, we found that linear and cubic spline interpolation over missing values and gaps in eye tracking data has a major impact on the classification accuracy of their LSTM model, to the point that overfitting occurred. This highlights the importance of further investigation into the impact of interpolation methods on the accuracy of LSTM or RNN models of different datasets to investigate generalizability.

2 RELATED WORK

First, we provide a short overview of the reasons for blinks and how blinks are used in systems for human-computer interaction (HCI). Next, we provide insight into different ways of blink detection. For the final part of our related work, we provide various ways of dealing with these blinks for machine learning methods.

2.1 Reasons for Blinks

Blinking is "a temporary closure of both eyes, involving movements of the upper and lower eyelids" [Blount 1927]. Human adults blink on average 12 times per minute, and one blink lasts roughly one-third of a second [Fatt and Weissman 2013]. Blinks protect the eye from drying out and regularly replenish the precorneal tear-film. However, there are a large variety of factors impacting the blink frequency of a human outside of these responsibilities, including but not limited to the time of day [Stern et al. 1994], the presence of air pollutants [Stern et al. 1994], monitors [Patel et al. 1991], contact lenses [Collins et al. 1989], perceptual load [Brookings et al. 1996; Tsai et al. 2007; Van Orden et al. 2000; Wolkoff et al. 2005], age [Stern et al. 1994], psychoticism [Colzato et al. 2009], and individual differences [Doughty and Naase 2006].

Various human-computer interaction (HCI) studies use blink data in interactive systems such as lie detection [Leal and Vrij 2008; Mann et al. 2002], driver fatigue detection [Bergasa et al. 2006; Hernandez-Ortega et al. 2019b], detection of mild cognitive impairment [Ladas et al. 2014], anti-face spoofing [Galbally et al. 2014; Hernandez-Ortega et al. 2019a; Pan et al. 2007], and human-computer interfaces [Acien et al. 2020] among many others. However, as the frequency of blinks is influenced by many factors, the accuracy of these interactive systems can be heavily impacted.

2.2 Dealing with Blinks

Grootjen et al. [2023] highlights the importance of consistently handling missing data as it hinders the development of effective intelligent systems, limits reproducibility, and can even lead to incorrect results. Although there are various parsers available for detecting and dealing with blinks, in Grootjen et al. [2024], the authors found that these are not always used and that the general way of dealing with blinks in eye tracking data is inconsistent. Furthermore, they compare different infilling methods for missing data and the error these methods produced in a set of artificially introduced blinks. In their work, the compared infilling methods were extracted from a literature review. They found that linear and cubic spline interpolation within the missing data produced the slightest error and that artifacts from blinks affect the eye movements 70 ms preceding and 118 ms following a blink.

2.3 Long Short-Term Memory Neural Networks

Long short-term memory (LSTM) is a deep neural network architecture that can classify time-series data. This technique benefits over traditional machine learning as it does not require domain-specific knowledge as it benefits from representation learning. This might be the reason for its rise in popularity in the physiological signal space. An example is the work of Pham [2021]; here, they used it for classifying ECG data. Moreover, it has also been gaining popularity in the eye tracking community (e.g., Bremer et al. [2023]; Hassan et al. [2022]; Palacios-Ibáñez et al. [2023]; Stein et al. [2022]).

3 METHOD

We base our analyses on the data and scripts from Annerer-Walcher et al. [2021] to evaluate the different infilling methods. We selected this dataset as, from their work, they provide both their data and model structure open-source on https://osf.io/scmry/. Their dataset consisted of binocular eye tracking data, including x and y-screen-based coordinates and pupil dilation. It contains information on conditions internal and external focus vs. verbal, numerical, and visuospatial tasks (two conditions × three tasks). They investigated how consistently different eye parameters respond to internal versus external attentional focus across the three task modalities (verbal, numerical, and visuo-spatial). They report that classifying the focus of attention worked well across participants but that generalizing it across the different tasks had proven challenging.

We use their data and model structure to evaluate the impact of the different infilling methods from peer-reviewed work. As such, we ran their scripts in 3 fold, once without changes, once where we linearly interpolated the gaps and once where the interpolation was done using a cubic spline method, without altering their scripts to preserve the validity of our work. These are the recommended infilling methods as by Grootjen et al. [2024]. Following those guidelines, we removed 70 ms preceding and 118 ms following missing data, as the blink can affect these. We used scripts containing the interpolation methods and removed the data preceding and following a blink from Grootjen et al. [2024], as these are openly available on https://eyetrackingguidelines.github.io/.

3.1 Pre-Processing the Data

To preprocess the data, we leveraged the existing scripts from Annerer-Walcher et al. [2021]. These existing scripts allowed us to read the different files that are part of the main task. They also provided training before the main task on their open-science framework repository. Even though we could not find in their code that this explicitly was excluded, we assumed it was and thus only used the files from the main task. The SMI RED250mobile system (SensoMotoric Instruments, Germany) with a temporal resolution of 250

Hz, a spatial resolution of 0.03°, and gaze position accuracy of 0.4° that they used for their experiment, writes 0 in the file whenever the eye tracker cannot find the pupil[1]. To leverage the existing scripts for interpolation from Grootjen et al. [2024], we replaced all of the "zeros" with "Not a Number's" (NaN).

3.2 Missing Data

Figure 1a presents the results of the consecutive NaN's logged. In the work of Grootjen et al. [2024], they showed that the closed eye time does not go beyond 1 second. As such, we have split the dataset into different parts once this happens, as the assumption here would be that there is missing values for other reasons than a blink. When looking at the remaining consecutive NaN's in the data we can see that this follows a similar pattern as the one visualized in Grootjen et al. [2024]; Holmqvist et al. [2011]. We use a Generalized Inverse Gaussian distribution [Perreault et al. 1999] to model the distributions of the lengths, see Figure 1b. Our regression models yielded an R^2 value of 0.51.

3.3 Gaps in the Recording due to Eye-Tracker

When visualizing the data, we found jumps in time that do not follow the 8 ms gap of the 125 Hz recording. Jumps in time between samples were on average 11.9 ms long with a standard deviation of 234 ms. In Figure 2, we visualize the number of seconds between two lines being logged into the different files in seconds that are over 8 ms (+ 10%). In total, the dataset contains 78.755 gaps in recording that are over this limit (m = 1324.9 ms, std = 4076.2 ms).

While sensors, such as eye trackers, deliver samples at a given frequency, the time is typically not precise. It can even happen that one or multiple consecutive samples are arbitrarily dropped. For this reason, we standardize the sampling frequency to perfect 125 Hz to counteract these gaps in the eye tracking data. Thus, we resampled the data to be exactly $1/frequency = 8msec$ apart. This allows us to investigate potential missing samples and gaps in the data and, thus, test infilling methods. During this process, we did not infill data; we merely ensured a perfect sample frequency of 125 Hz. If a sample was missing in the original dataset, the data was added at the correct time and marked as NaN for later processing using the different infilling methods.

4 RESULTS

In total, the dataset has 78.755 gaps in the recording where the eye tracker did not log any data and 52.219 sections of data where there were consecutive 0's (by us converted to NaN's) logged because the eye tracker was not able to recognize the pupil. We then resampled the data frame to allow for consistent steps in time according to the 125 Hz logging in the remaining of data. We then split the dataset in parts where there were more than 1500 consecutive NaN's in the dataset as the long short-term memory (LSTM) neural network (NN) provided by Annerer-Walcher et al. [2021] takes in a window of 1500 samples. In the initial dataset, having 1500 or more consecutive 0's happening only existed nine times; after our pre-processing, this happened 1198 times.

We infilled the dataset linearly and used cubic spline to fill in the remaining gaps in the data. For the cubic spline infilling, we take three samples at the start and end into consideration to allow the cubic spline interpolation to consider the velocity. If there was a gap of a single sample during the cubic spline interpolation, we linearly interpolated this, as cubic spline interpolation is not warranted in these scenarios. If there are NaN's in the 3 samples before or after the gap, we recusively go back or forward, respectively, until we find the allotted samples without NaN's. After interpolating, we had 3 datasets, one as provided and processed exactly by Annerer-Walcher et al. [2021], one linearly interpolated, and one cubic spline interpolated. These interpolation methods were applied over x and y screen-based coordinates for both eyes and the pupil dilation values for both eyes. Both of the interpolated datasets were without any missing samples or NaN's remaining.

In the work of Annerer-Walcher et al. [2021], they have used 157 participants from the whole dataset and excluded 9. Of this data, 135 sessions were used as training data to adjust the model parameters, and the remainder were used as testing data, pooling data from all tasks. Unfortunately, we could not identify in their publication or from the OSF page which participants were excluded and which sessions were used for which purposes. As such, we split the whole dataset, using a fixed seed, based on all participants (166), using 60% of the participants (99) for training, 20% for testing (33), and 20% for validation (33). We used the existing processing scripts after the infilling to generate the input for the LSTM model. We left the model's hyperparameters unchanged in the code.

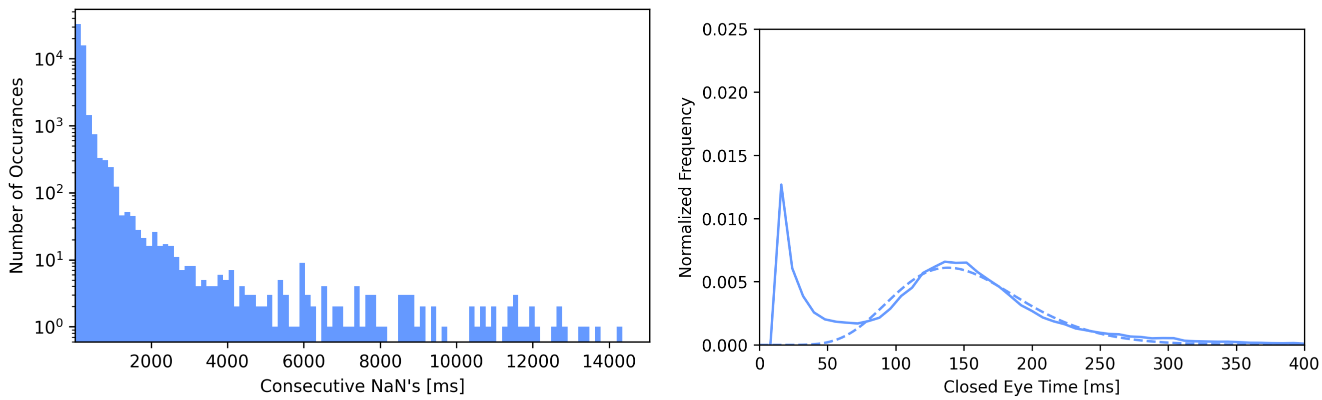
As such, our model starts with the input layer of 1500×16, followed by an LSTM layer of 64 units, after which there was a dense layer present of 64 units with a ReLu activation function with a dropout layer of 0.45 following the dense layer. After the dense layer, the model contains a convolutional layer followed by a max pooling layer as 1D. The final two layers contain another LSTM layer of 32 units and a final dense layer of 2 for the output. The model uses a nadam optimizer with a fixed learning rate of 0.001. The models were trained over 40 epochs in batches of 30 with an early stopping rule and a patience of 3 on the validation loss.

Our reference model yielded a training accuracy after five epochs of 0.8713, a test accuracy of 0.7699, and a validation accuracy of 0.7863. We achieved this with 6813 sets of windows for training, 2490 sets for testing, and 2176 sets for validation for 11,479 sets of windows. The model after linear interpolation yields a training accuracy after six epochs of 0.8834, a test accuracy of 0.7732, and a validation accuracy of 0.7946. We achieved this with 8765 sets of windows for training, 3157 sets for testing, and 2795 sets for validation for 14,717 sets of windows (28.2% more data over default). Our final model using spline interpolation yields a training accuracy after seven epochs of 0.9023, a test accuracy of 0.7555, and a validation accuracy of 0.7599. For this, we had 8732 sets of windows for training, 3141 for testing, and 2790 sets for validating (27.7% more data over default).

5 DISCUSSION

In this work, we applied two recommended interpolation methods from past work used to infill the missing data on a publicly available dataset. Our findings show that these interpolation methods over missing data points and gaps in data recording have major implications for the accuracy of the LSTM model provided with

[1] https://www.dpg.unipd.it/sites/dpg.unipd.it/files/BeGaze2.pdf, accessed 2024-04-05



(a) Consecutive NaN's **(b) Closed Eye Time**

Figure 1: (a) The log-scaled distribution of consecutive NaN's appearing the data. (b) We visualize the normalized frequency closed-eye time for the dataset. The dashed line represents an inverse Gaussian probability density function fitted to the data ($R^2 = 0.51$)

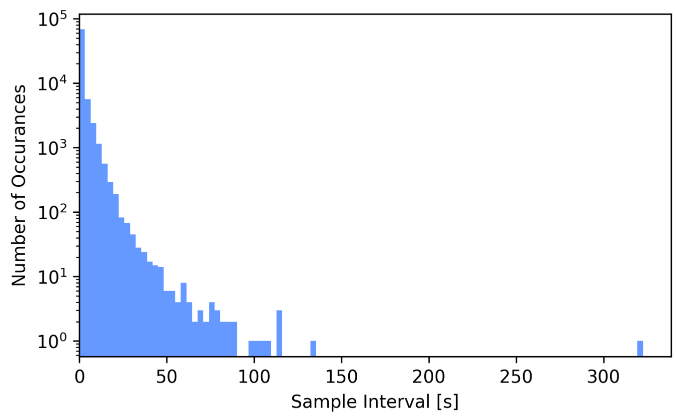
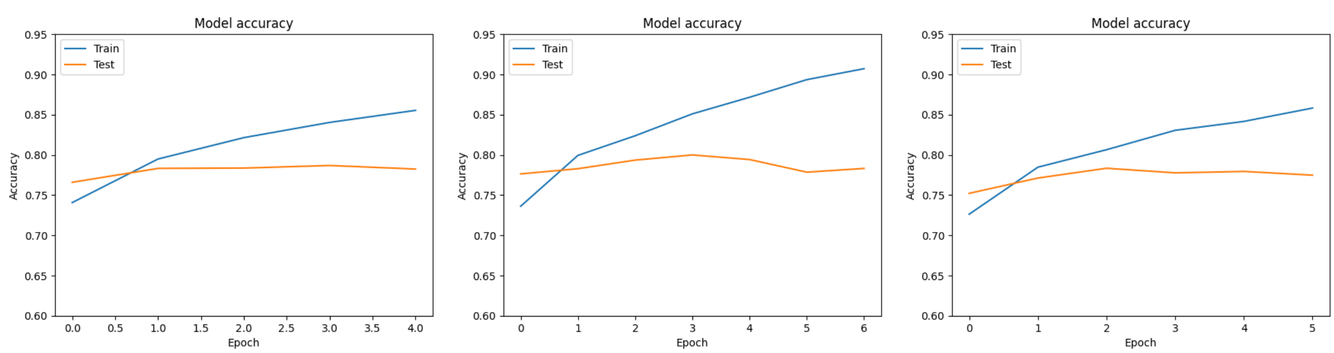
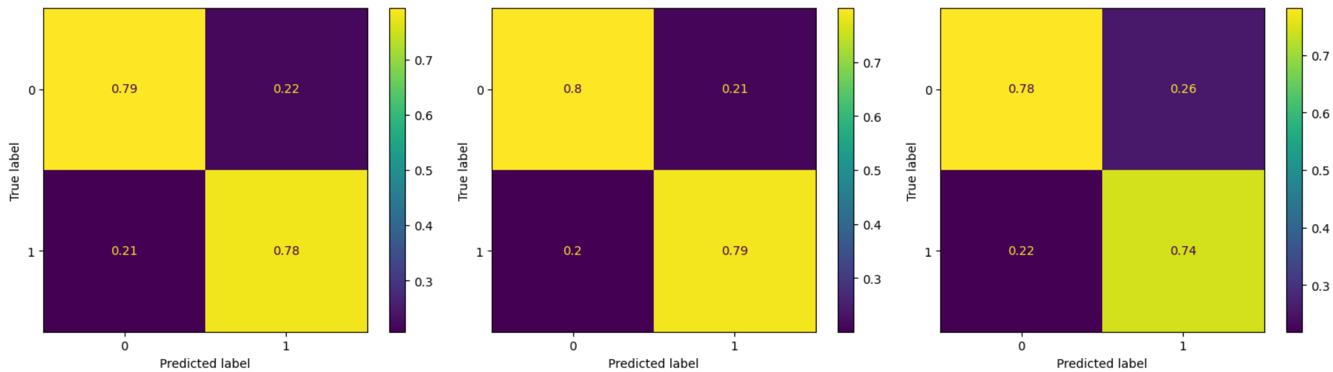


Figure 2: Illustration highlighting the interval (time between) of the logged samples over 8.8 ms (which should be the normal interval of a 125 Hz recording + allowance of 10% in variation).



(a) Default **(b) Linearly Infilled** **(c) Cubic Spline Infilled**

Figure 3: The train and test accuracy for the three models we trained. (a), shows the training and validation accuracy plotted for the default dataset. (b) and (c) show these for the linearly interpolated data and cubic spline interpolated data, respectively.



(a) Default **(b) Linearly Infilled** **(c) Cubic Spline Infilled**

Figure 4: Confusion Matrices from all the predictions on the validation sets (20% of the participants) using the provided model structure and input length. (a), shows the confusion matrix for the default dataset. (b) and (c) show these for the linearly interpolated data and cubic spline interpolated data, respectively.

the dataset. To the point that overfitting happens if we keep the original model structure.

Overfitting happens due to a modeling error when a function is too closely aligned to a limited set of data points. As a result, the model is useful only for reference to the initial data set and not to other data sets. In other words, it is not generalizable. We can see this in Figure 3, where the models all have an increase in training accuracy, while the test accuracy is almost stationary. We expect this to be in part related to not being able to reproduce the results of the previous work completely, as the exclusion of participants was not available to us, and neither was the split in data used for training and test purposes. Furthermore, the work documentation suggests that the experiment was recorded at 250 Hz, while the published data set suggests this was recorded or down-sampled to 125 Hz.

Infilling data comes at the "cost" of knowing the future sample. Only gaps can be interpolated using infilling methods. However, in interactive systems, this is not always the case; e.g., during a blink, a future sample for interpolation is not known. For this, we will need to experiment with extrapolation methods. Extrapolation in interactive systems is nothing novel and has even been done using neuronal networks for touch input [Henze et al. 2017]. However, a future real-time implementation of our approach will need to address the challenges of the "unknown" future.

6 CONCLUSION

In conclusion, interpolation methods are powerful for handling missing data and gaps in eye-tracking studies. We argue that the recommended interpolation methods should be preferred over leaving gaps in the recording or removing that data, as these can have huge implications on the available data as highlighted in Grootjen et al. [2024]. Both linear and cubic spline interpolation provide ways to improve the provided model's accuracy. Here, tweaks could boost the accuracy even further without overfitting the model on the training data, as there is an increase of over 25% in data available for the model. Future work should investigate the generalizability to other datasets.

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