Tomography of Rotated Bunches at PS Extraction

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Abstract

One of the limitations to reach the beam parameters of the LHC Injector Upgrade project are the losses occurring at transfer from the PS to the SPS. To reduce the losses, a good knowledge of the effective machine settings and particle distribution is required. A tool used to both reconstruct the longitudinal distribution of the beam and get the effective machine parameters is beam tomography. In this work, tomography was used to evaluate the RF phase error during bunch rotation, but did result in errors of up to ± 10 degrees. Machine learning is being investigated as an alternative method to gather this information.

1 Introduction

1.1 Motivation

The longitudinal beam transfer from the PS to the SPS is a delicate process. In order to successfully transfer the bunches from the long PS RF bucket (25 ns) to the short SPS RF bucket (5 ns), the bunches need to be shortened. A special scheme called bunch rotation is implemented in the PS [1]. The bunch rotation consists of a fast increase of the RF voltage to rotate the bunch in phase space, converting the long bunch with small energy spread turn into a short bunch with large spread. The present scheme relies on the usage of four RF stations: two systems tuned at 40 MHz (rf harmonic 84) and two systems tuned at 80 MHz (rf harmonic 168), each of them able to deliver an RF voltage of 300 kV. The voltage is increased in two steps, first with the 40 MHz cavities then with the 80 MHz cavities. Due to the non-linearities of the RF voltage, not all particles rotate in phase space at the same speed and the bunch is injected in the SPS with an "S-shape". The result of this process is illustrated in the Figure 1. The red particles represent the section of the bunch where particles are outside of the new bucket, so are not captured in the SPS, the orange represents the particles that will be lost gradually in the SPS, and the blue represents the particles which are successfully captured.

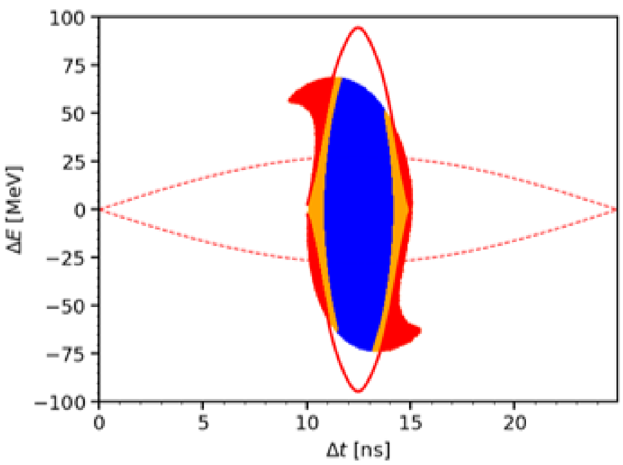


Figure 1: Longitudinal phase space plot of the bunch at injection into the SPS. The RF bucket before bunch rotation in the PS is shown as a dashed red line, while the SPS RF bucket at injection is shown as a full red line. The bunch is S-shaped due to the non-linearity of the bunch rotation in the PS, and particles will be immediately lost (red), slowly lost (orange) and captured in the SPS (blue).

In the framework of the LHC Injector Upgrades (LIU) project, the beam intensity will be increased by a factor of two [2]. A limitation is that the losses at SPS injection are increased beyond an acceptable level (the project baseline is 10%), and should therefore be minimized. One of the possible reasons of the increased losses is the shift of the effective machine settings like the relative RF phase between the 40 MHz and 80 MHz RF systems during bunch rotation. This means we have to better understand the path of particles within the accelerator and the development of the shape of the bunch. The goal of this project was to study whether tomography in the PS is a reliable tool to evaluate for the relative phase error during rotation.

1.2 Tomography Convergence

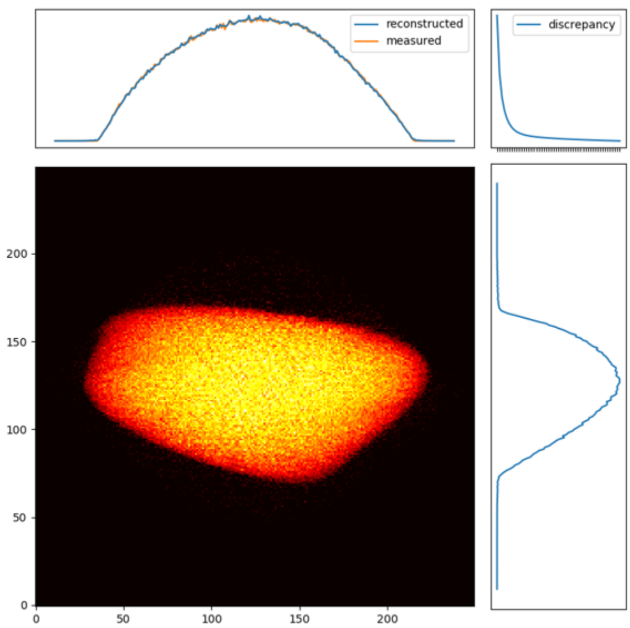


Figure 2: Example of reconstructed bunch distribution in longitudinal phase space using tomography. The top plot shows the measured profile at a given turn and the corresponding reconstructed profile, the right plot shows the distribution in energy of the particles. Top right figure indicates convergence of the iterative tomography process.

The distribution of the particles within a bunch in phase space $(\tau, \Delta E)$ where τ is the longitudinal position of a particle and ΔE is its energy relative to the design value, cannot be directly measured. Indeed, only the bunch density in the longitudinal direction can be measured. This profile corresponds to the projection of the particle distribution from the 2D phase space $(\tau, \Delta E)$ to the 1D longitudinal dimension τ. The particles rotate in phase space, performing so called synchrotron oscillations. Therefore, each measured profile as a function of time corresponds to a projection at a given angle of the longitudinal density in phase space. Each projection can be used to reconstruct the longitudinal density in phase space using tomography. The present algorithm was improved by including the non-linear synchrotron motion by tracking particles [3].

The present implementation of longitudinal tomography at CERN is an iterative process which means for each step the discrepancy reduces, until it asymptotically reaches a minimum value (see Figure 2). The quality of the reconstruction depends on a correct representation of the synchrotron motion, i.e. to a good knowledge of the machine parameters such as the RF voltage and phase, which may shift from the set value. A method used routinely at CERN consists of scanning the parameters used for the tomography algorithm, to find for which set of parameters the reconstruction is the best, using the convergence as a figure of merit [4]. In this project, this method was used to test the accuracy in identifying an error in the relative RF phase between the 40 MHz and 80 MHz RF systems during bunch rotation.

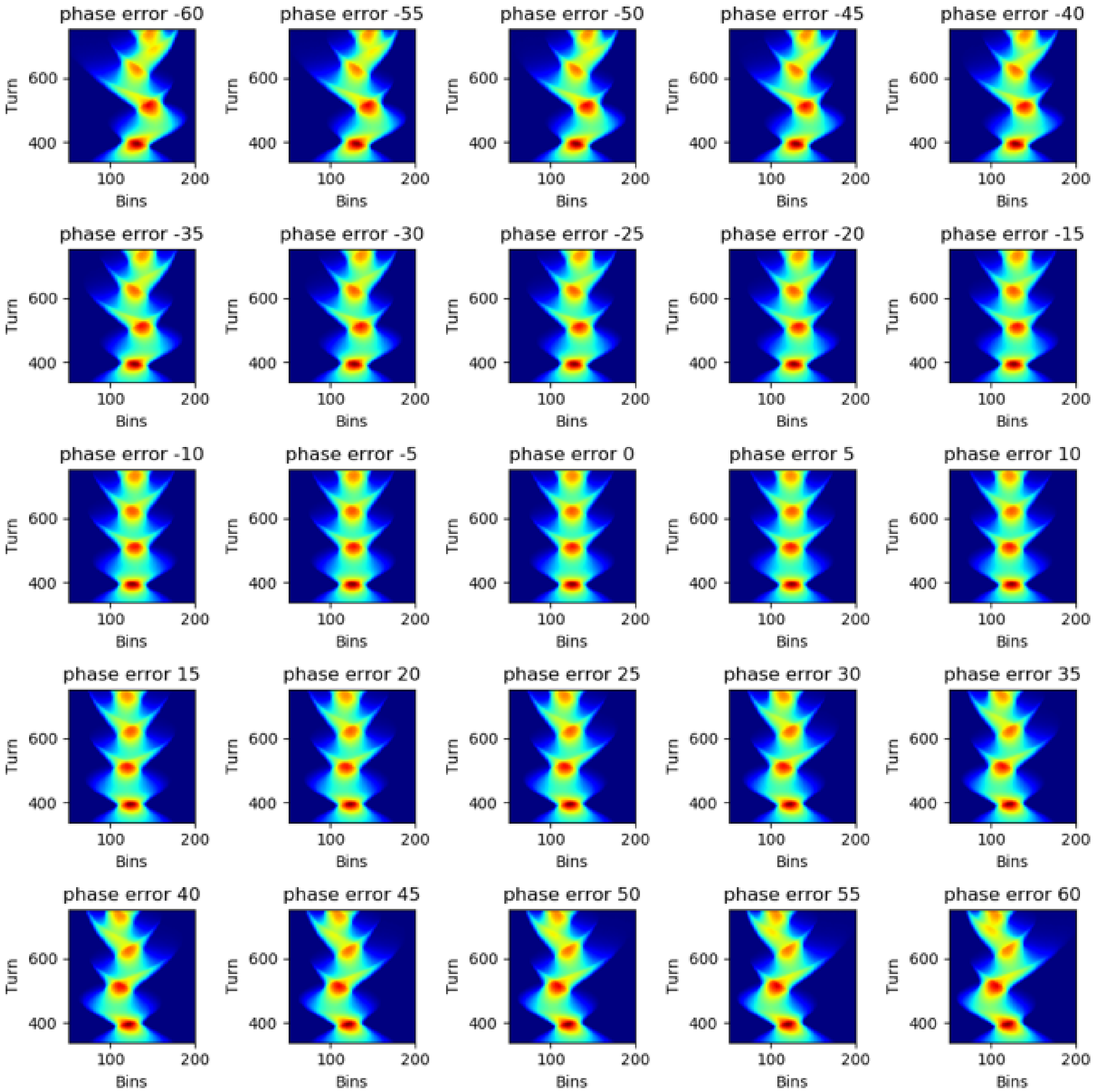


Figure 3: Bunch profiles represented as mountain range plots for different relative phase errors (in degrees) set in simulations.

2 Method

2.1 Simulation

The tracking code BLonD [5] was used to simulate the bunch rotation, including a relative phase error as an input. The bunch profiles were gathered and stored as arrays. In normal operation, the bunch is extracted to the SPS when the bunch length is the shortest. For the tomography, the bunch is left to oscillate for about 2 synchrotron periods to get all projection angles.

The profiles can be represented as mountain range plots as in Figure 3 for a visualisation of the development of bunches. They can then be used as an input to find the deviation from the tomography code's prediction of the phase error compared to the actual phase error assumed for the simulation. An assumption for the center of the RF bucket (i.e. synchronous phase) must also be passed to the tomography algorithm. A byproduct of the relative phase error during bunch rotation is that the synchronous phase is also shifted and should thus also be scanned.

Nested loops were implemented to scan across a range of combinations of values for phase error and synchronous phase to find the one that gives the minimum discrepancy, as this is the best combination. For each set of input RF phase and synchronous phase, these parameters are then stored and can be compared to the minimum value of discrepancy for different input values. The ideal scenario would be that the minimum value for discrepancy would give a result for the RF phase and synchronous phase which reproduces the original value input as a simulated error in the tracking code. If this method is successful in simulations, the method could then be applied to evaluate the relative phase error during bunch rotation with measured data.

3 Results

3.1 Simulation Results

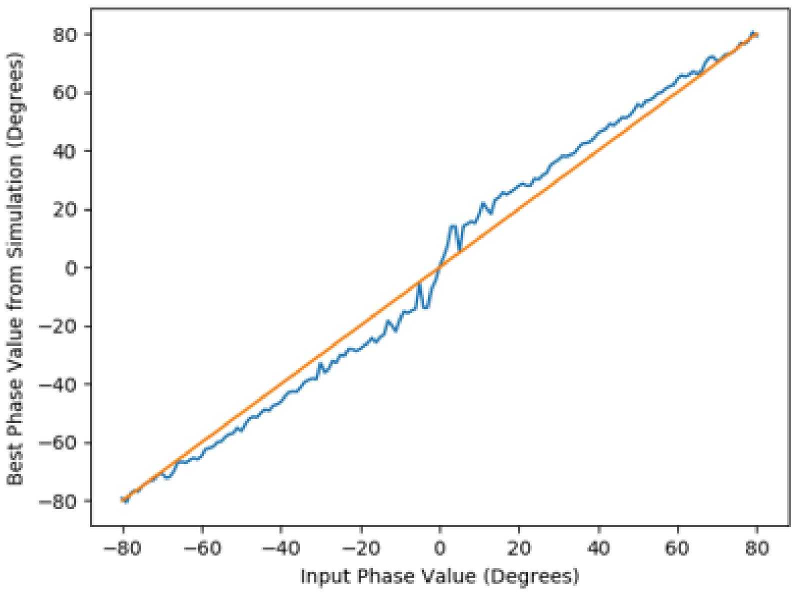


Figure 4: Input phase value versus expected phase value from simulation. The blue line represents the predicted values with tomography, while the orange line shows the expected output.

The optimum phase value determined by the simulation was reasonably close to the input phase value, as can be seen in Figure 4. The best fit occurred when the input phase was 0 degrees and when the input phase was high $> \pm 60$ degrees. There is a slight asymmetry between the positive and negative phases. This could provide an estimate of the numerical error, since the problem is expected to by symmetrical with respect to the case where the input phase error is zero. Overall the tomography code's predictions follow the desired trend.

However, when looking at actual deviations from the input value (Figure 5) the deviation is between $\pm$ 10 degrees from the actual input value. This is a comparatively large error, especially for expected

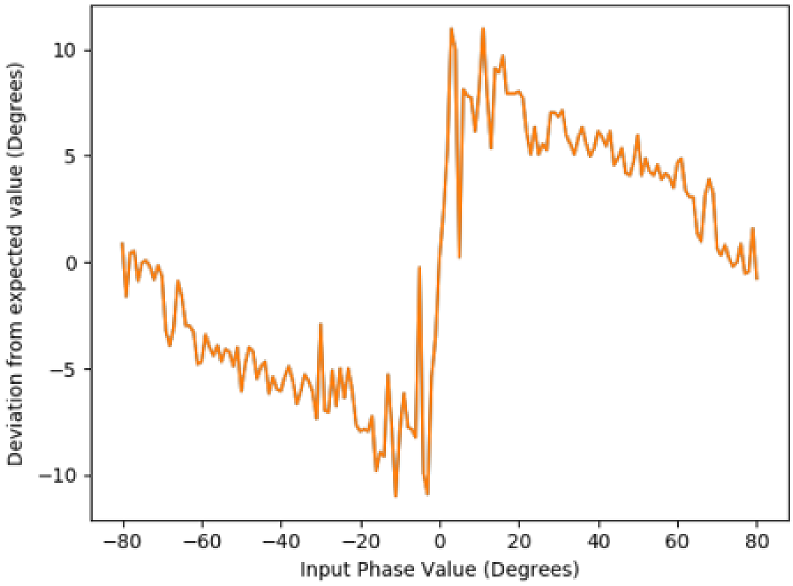


Figure 5: Discrepancy between the expected value for input phase and the value predicted using tomography.

small phase errors which are more likely to occur due to systematic errors in the machine.

3.2 Error Between Prediction and Result

We further investigated the source of the error in predicted values by producing density plots (Figure 6) of the minimum discrepancy. On the same plot is marked with a red line the expected minimum value of phase error (i.e. the input value) and the actual value of the minimum that the tomography scan produces with dots. Note that the axes were scaled to represent the relative phases and the synchronous phase using the same units (degrees with respect to the frequency of the 40 MHz RF system).

This figure confirms the results discussed above. The actual value and that predicted using tomography are very close for zero and large phases, but there is a significant discrepancy for values around zero.

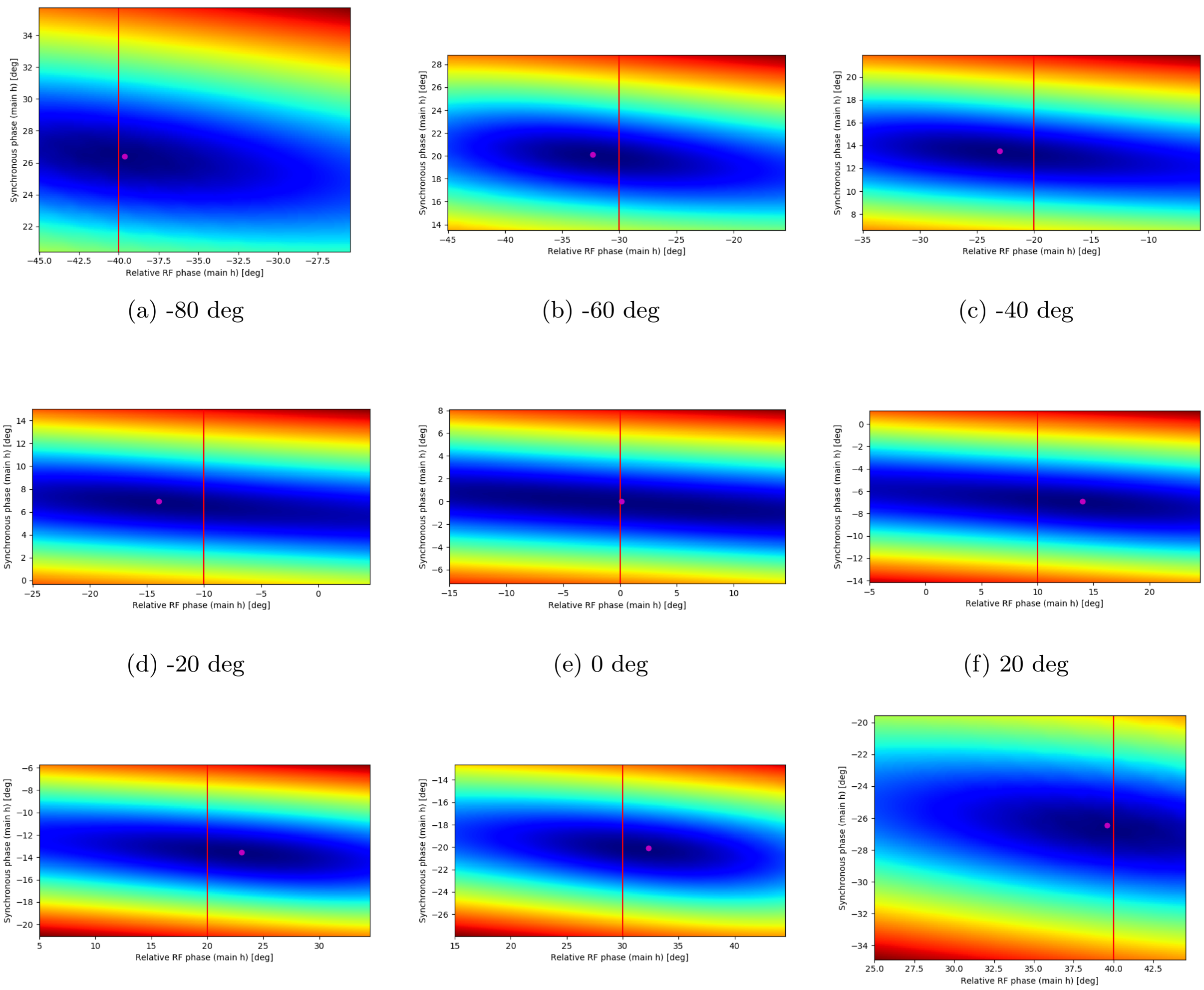
3.3 Interpretation

A small change in the relative RF phases does not change the value of the divergence by much as can be seen by similar values on the density plot across many RF phase values. However, a small variation in the synchronous phase gives a much larger change in the minimum of divergence. A small error in synchronous phase is dominant and results in a poor accuracy to find the relative phase error for the RF systems. It appears that a perturbation on the synchronous phase has an influence on the tomographic reconstruction leading to a too low sensitivity on the relative RF phase error, except if that one is very large.

4 Improvements

4.1 Machine learning, Computer Vision

A suggested improvement as an alternative to the current tomography tracking code is to use a machine learning algorithm to evaluate the phase error. The idea is to extract the phase error directly from the



(a) -80 deg (b) -60 deg (c) -40 deg

(d) -20 deg (e) 0 deg (f) 20 deg

(g) 40 deg (h) 60 deg (i) 80 deg

Figure 6: Density plots for each input phase value. The colorscale correspond to the convergence of the tomography, the dot to the minimum convergence value, and the vertical line the input phase error for the simulation.

features visible from the waterfall plots (e.g. bunch asymmetry). Computer vision is a process in which a computer can be trained to identify different shapes as particular objects, or in this case particular phase error inputs.

A basic convolutional neural network (CNN) was set up to test whether machine learning would be an effective way to evaluate the phase error. The CNN was built with two stages of convolutions with different kernels which purpose is to find local features in the image. Each stage directly followed by a max pooling process which consists of downsampling the image size. After the convolutional part to extract the relevant features from the image, all pixels after the last max pooling are connected as one linear array. All nodes of the last array are connected to provide with a single output value, which encodes the image into the corresponding calculated phase error. An example is shown in Figure 7. Note that a Rectified Linear Unit (ReLU) function was used as activation function for this CNN. The CNN was then trained using 80% of the mountain range plots produced with the simulations described above, while the remaining 20% of the data was used for testing.

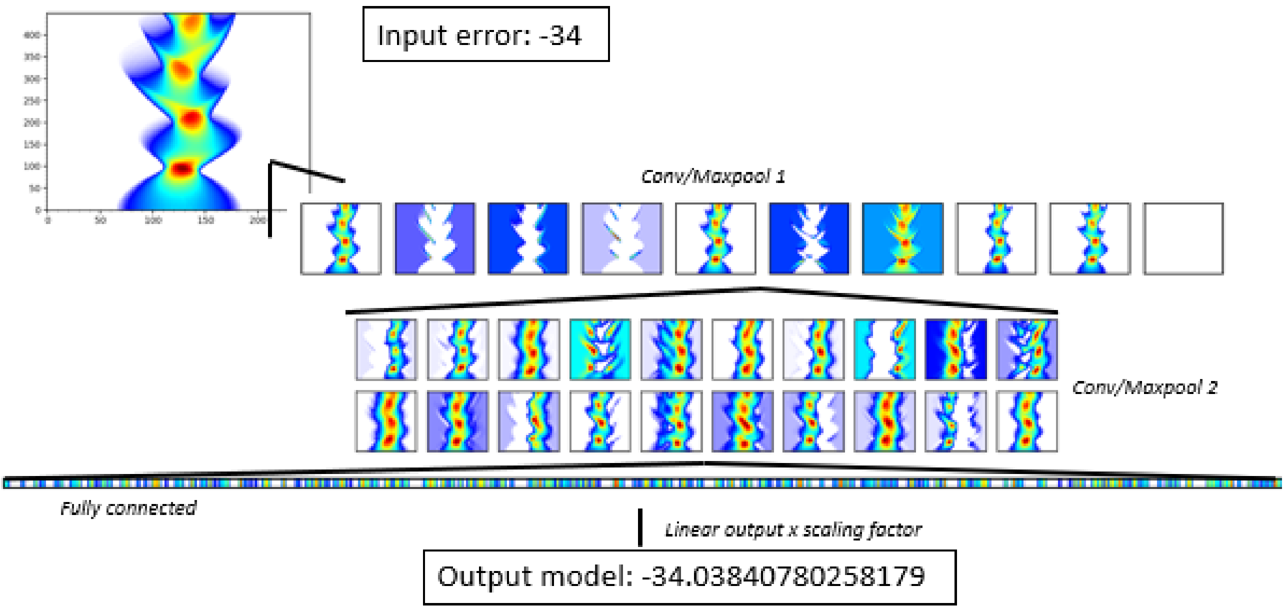


Figure 7: Example of a trained Convolutional Neural network run with an input waterfall which was produced with a -34 degrees phase error. The output of the model is the reconstructed phase error that was identified by the network, based on the features it extracted from the waterfall image.

4.2 Results of Machine Learning with a Trained Convolutional Neural Network

The result of the training is shown in Figure 8 with the label "Full data". The reconstructed phase error is accurate down to <1 degree. As a more concrete illustration, the first run of the neural networking successfully identified a phase input error of -34 degrees (Figure 7) with only a very small associated error of 0.038 degrees. This is a huge improvement compared to the $\pm$ 10 degree error from the tomography method.

4.3 Future Development

A test was done to see if the machine learning method could find the phase value where only partial information was available. Indeed, in normal operation, the bunch would be extracted when it is the shortest and therefore we would only have partial information. Hence this method would be extremely

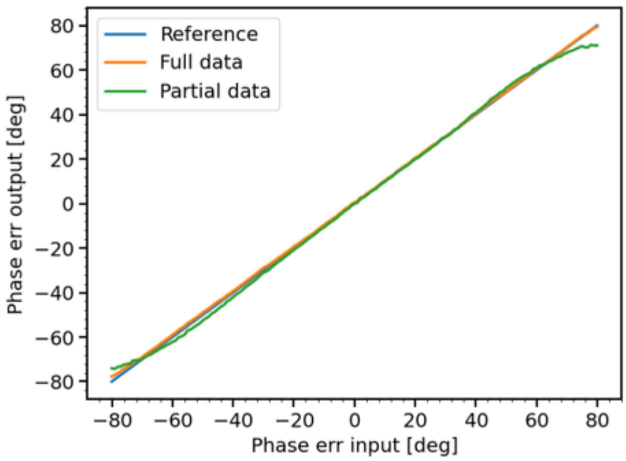


Figure 8: Output of the CNN trained with the same simulated data as used for the tomography as a method to find the relative phase error. The output phase error of the CNN for a given input waterfall is compared to the expected value (Reference), for cases where complete synchrotron oscillations are given (Full data), or when the bunch is extracted to the SPS (Partial data).

attractive as it does not require changing any machine parameters and could be applied to parasitically recorded measurements. Passing data where the bunch is extracted to the model trained in the previous section exclusively with data where the bunch is not extracted was unsuccessful. Additionally, training the CNN exclusively on data where the bunch is extracted was not successful as well.

Nonetheless, there is scope for future development improving the neural network so that it could recognise phase errors from partial data sets. This was done via a a method comparable to data augmentation[1]. The principle here was to train the neural network with partial data corresponding to the bunch extraction, in addition to full data from when the bunch is left to oscillate in the PS. The result of the training with augmented data and passing an extracted bunch to the neural network is shown in Figure 8 with the label "Partial data". This gave a good convergence making it a promising candidate to look into for future honing of this method.

5 Conclusions

To minimize the fraction of the bunch distribution not captured during transfer between the PS machine and the SPS machine, one needs to find the initial phase error between the 40 MHz and 80 MHz RF systems during bunch rotation in the PS. Datamining of measured bunch profiles from the PS can be applied. While using tomography convergence gives a reasonably accurate value for the input phase it can have errors of up to $\pm$ 10 degrees associated with it, making it a candidate for an area of improvement. The machine learning method provided a much more accurate result, however further work needs to be done on it to increase its accuracy when dealing with partial data sets and should to be tested with real measurements with noisy profiles.

[1] Data augmentation is a classical method in machine learning and consists of modifying the existing data while keeping its main features to extend the dataset (e.g. for a neural network classifying animals, a mirrored or rotated image of a cat is still a cat, hence the same image can be reused several times).

References

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