Evolutionary NAS for Topology of an Acoustic Propagation Predictor

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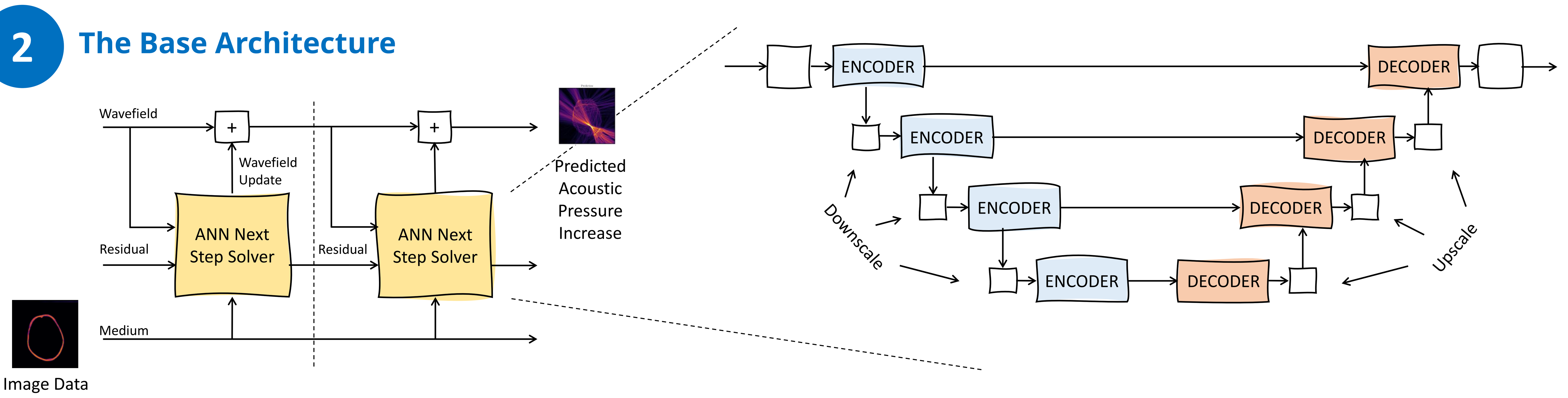
1 Introduction

To find an optimal treatment plan for a High Intensity Focused Ultrasound surgery a multitude of computationally expensive simulations need to be evaluated, often thousands of times to obtain a precise treatment plan. Recent renaissance of machine learning technologies could provide a solution to this problem, as a recently published article presented a Physics Informed Neural Net to predict Acoustic Propagation through a human skull. While the net utilizes a UNet topology a is reasonably small, a multiple redundant parts are present within the design and the whole approach was to prove this approach is feasible. To validate this net for use in HIFU treatment plan optimization loop, an attempt was made to try and find a different architecture for the net, minimizing the number of parameters while preserving the precision with use of a combination of genetic algorithm and cartesian genetic programming.

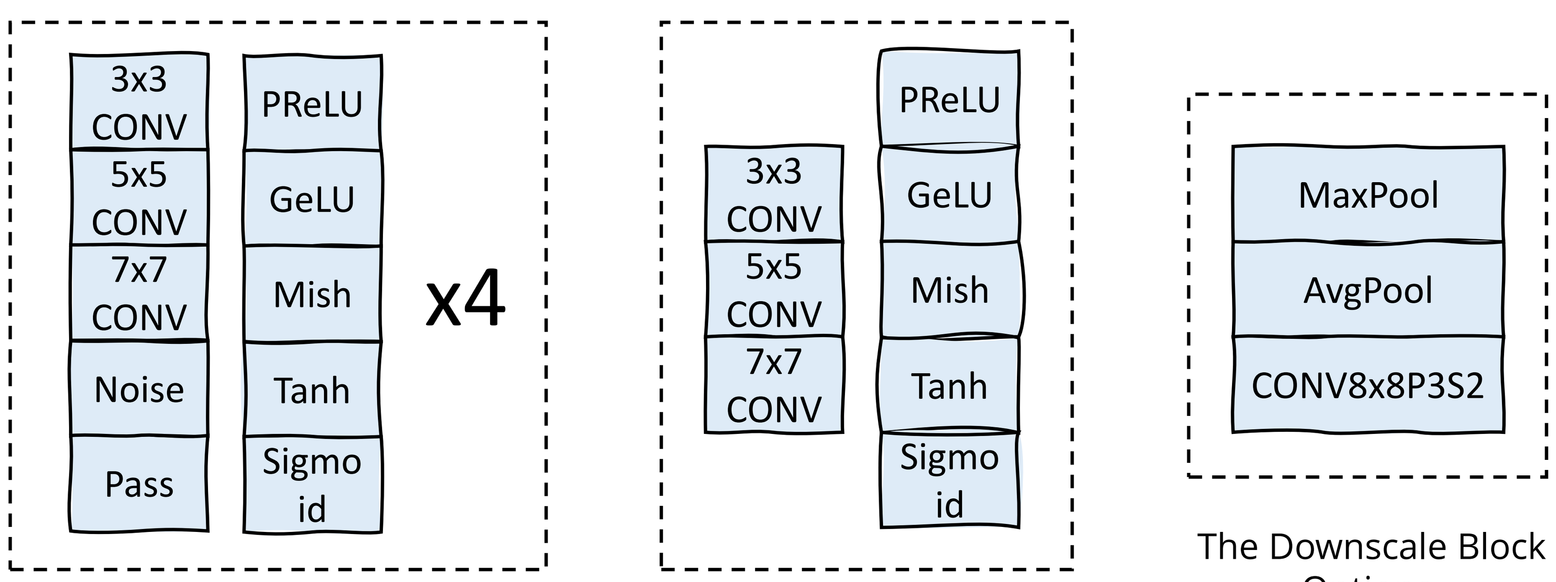
2 The Base Architecture



The state-of-the-art solution is currently using a recurrent UNet architecture, consisting of merely 47k parameters and achieving precision in order of 10^{-5}.

3 The Encoder and Decoder Block Phenotypes

To find the Encoder-Decoder inner architecture, a CGP was employed. Both blocks consist of a cascade of 4 operations, each followed by an activation function. In addition, each encoder segment contains a feedback memory block storing the cumulative result of previous iterations.



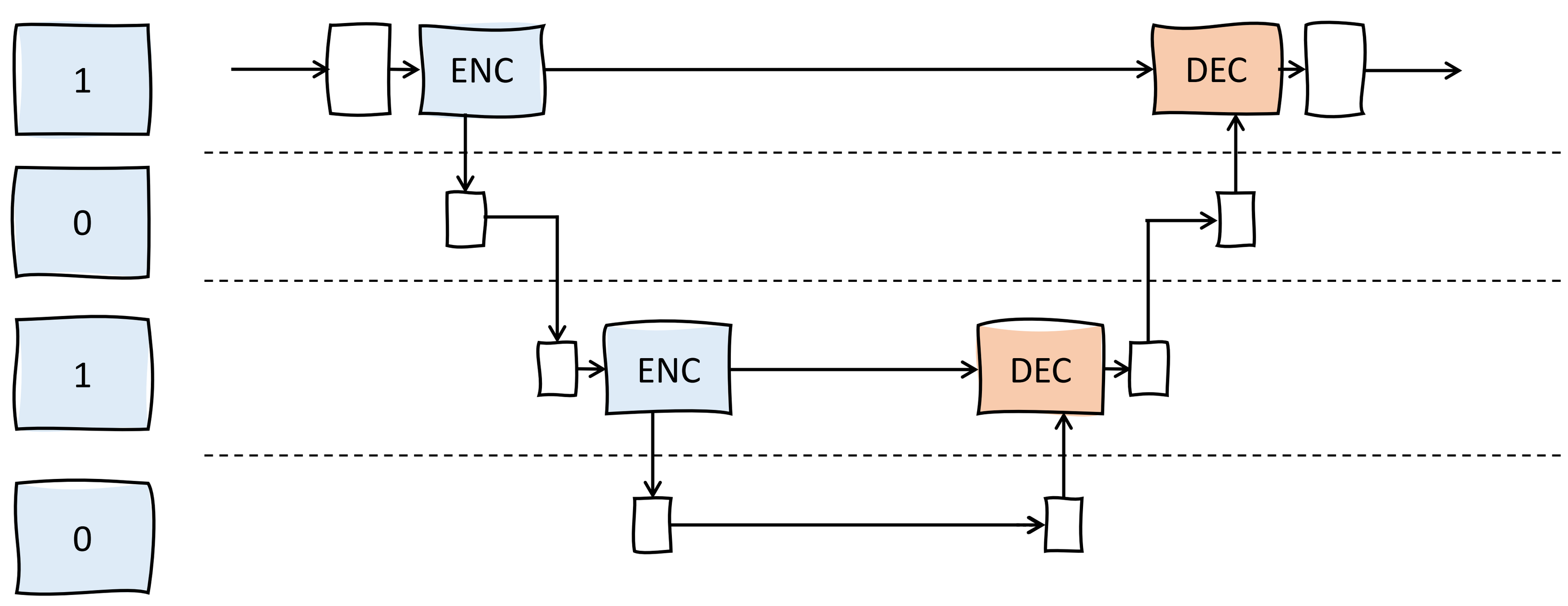
The Encoder and Decoder Block

The Encoder Memory Block.

The Downscale Block Options.

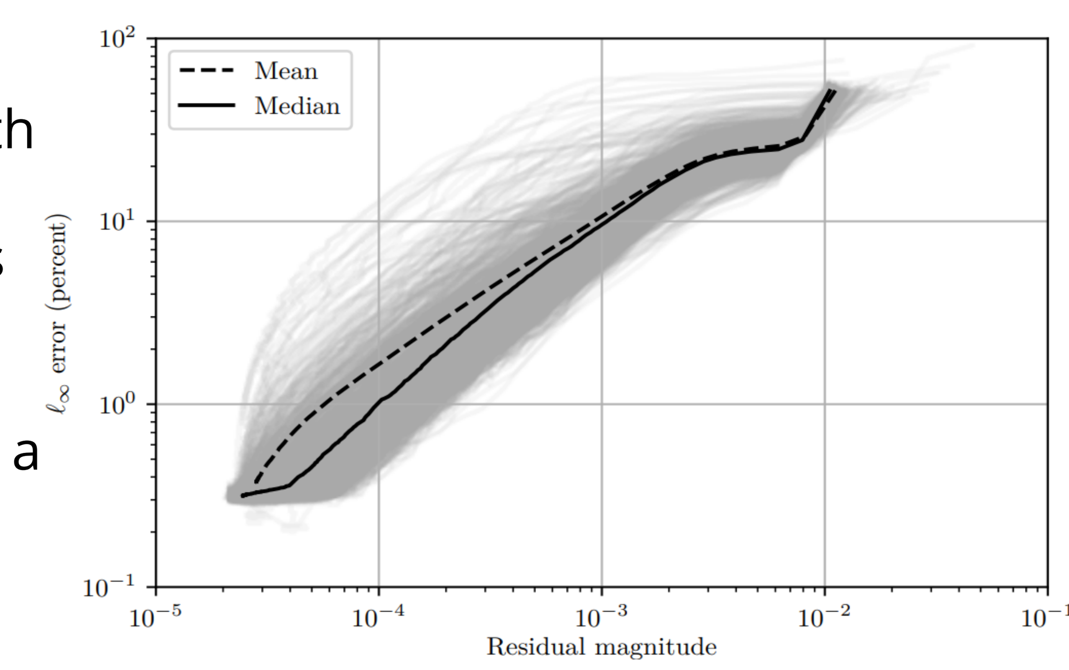
4 Layer Disabling

In tandem with the CGP evolution of Encoder-Decoder blocks, another cooperative EA is evolving a short binary genome, encoding which layers of the UNet are disabled. At least one layer needs to be always enabled.



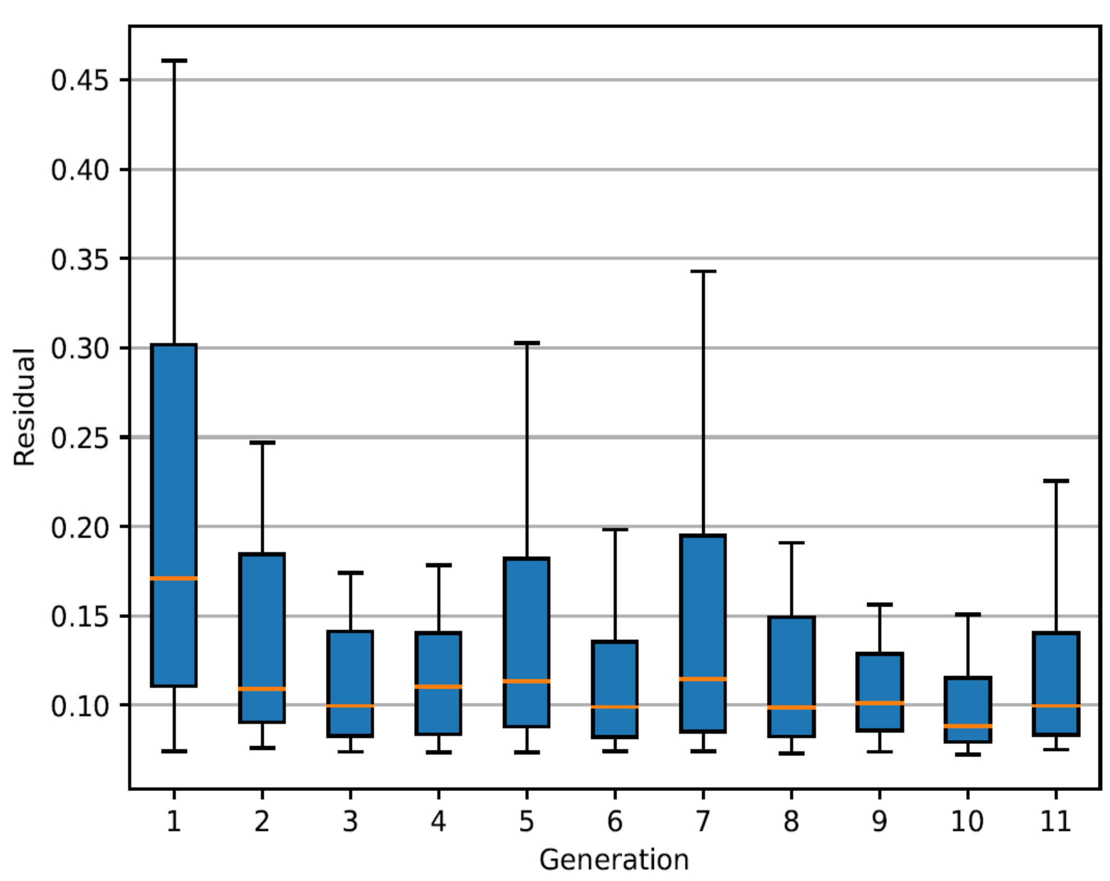
5 Search Setup

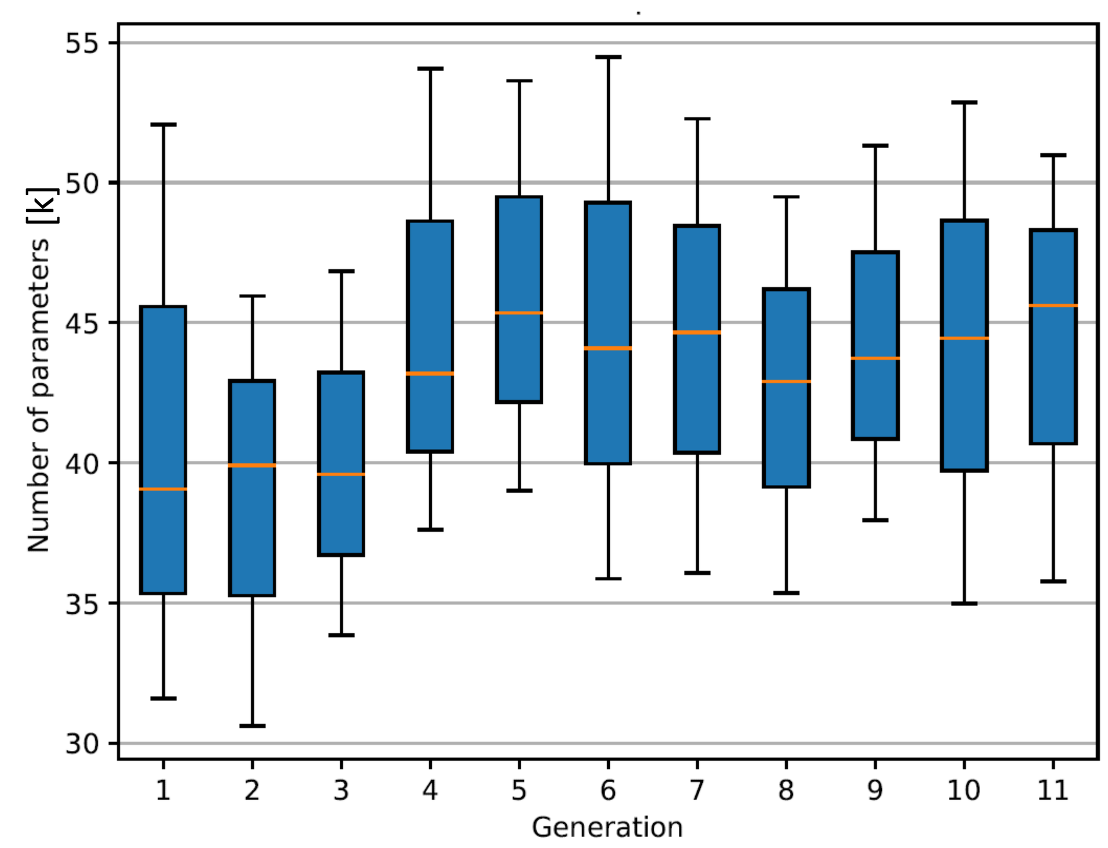
For the first attempt, we are running 12 generations each with 50 individuals. Each candidate network is trained for 5 epochs and the residual of the net then used as a fitness. Main genetic operator used was mutation, crossover was omitted.



6 Preliminary Results

We can observe that the residual ofthe candidates is not moving much during the evolution. This could indicate an already solid base choice for the Encoder-Decoder blocks and the number of layers, especially when considered with the spread of number of parameters in each generation. Keep in mind that this presented is after training only for 5 epochs, instead of the final 1000.





7 Conclusion and Further Research

The base network proved to be designed with a solid foundation. When we took the best solution found during the search and trained it fully for 1000 epochs, the resulting residual was one order higher than the base net (sub 1% difference for the original net versus roughly 2% difference for the evolved one), but it had 7000 fewer parameters. In general, the better solutions during the search were the ones that disabled one or more of the deeper layers, showing a potential future research area.

k-Wave A MATLAB toolbox for the time-domain simulation of acoustic wave fields

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