**Слайд 1:**

Good afternoon! My name is Alexander Degtyarev. Today I`m going to focus on the topic: “Non-linear self-interference cancellation on base of mixed Newton method”.

**Слайд 2:**

Firstly I`ll give you an introduction to the In-band full duplex systems and self-interference cancellation. Then we`ll focus on the adaptive compensation of self-interference. And finally I`ll give conclusions and possible research directions.

**Слайд 3:**

Modern communication technologies require effective resources arrangement among the users. Also network reliability, low latencies and high data rates are required.

In this regard In-band full-duplex is promising approach which provides efficient spectrum usage by sharing bandwidth between transmitter and receiver.

However it suffers from self-interference cancellation.

**Слайд 4:**

Current slide represents full-duplex transceiver scheme. Due to the RF-chipset integral implementation and problems with isolation, TX-signal leaks to the receiver path. In addition, TX-signal is distorted by nonlinear components such as PA/duplexer and in linear leakage path. This distorted signal is called self-interference.

The main idea of self-interference cancellation is an identification of interference by minimization of mean square error.

**Слайд 5:**

Behavioral Hammerstein model is used as an interference model with adaptive parameters. It includes the part responsible for nonlinearity description and description of leakage path.

Hammerstein model describes physical process of interference creation and, as a result, it can effectively suppress interference with low computational resources.

**Слайд 6:**

Here we come to the mixed Newton methods. Mixed Newton is a second-order method which implies calculation of MSE gradient and mixed hessian for optimization step.

The method is designed work holomorphic error functions (error vector doesn`t depend on the conjugated model parameters). For holomorphic functions mixed Newton repulses from saddle points, which makes this method attractive.

However computational complexity of MNM is high due to hessian calculation and inversion.

**Слайд 7:**

For our simulations interference signal is obtained in the following testbench: we used real RF power amplifier for nonlinear distortion and digital FIR filter to simulate leakage channel.

In Hammerstein model we used polynomial model order 8 and FIR wit 45 taps.

**Слайд 8:**

Here we come to the simulation results. On current figures learning curves are introduced for stochastic and block gradient descent with different optimizers and Mixed Newton.

As we can see Mixed Newton require sufficiently less training epochs to achieve final performance comparing to gradient-based methods.

**Слайд 9:**

Current figure shows power spectral densities of initial and suppressed interference. In other words the distribution of interference power along the frequency axis.

**Слайд 10:**

Finally, current table represents convergence speed of MNM and considered common gradient methods. It can be seen that although optimization step of MNM is computed 5 times longer, total training time is significantly lower.

**Слайд 11:**

Conclusions:

Firstly: Total training time is decreased significantly comparing to common gradient methods.

However current method requires high memory and computation resources due to hessian calculation and inversion.

Further work may be focused on the simplification of Mixed Newton by hessian (or its diagonal) estimation.

Also, modified method may be applied for complex-valued neural networks training.