Deep Learning to Demodulate Transmissions in Molecular Communication

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I. Introduction

Implementations of Deep Learning can be found in a variety of application fields. Some examples are the use of Deep Learning for classification of handwritten numbers [1] or in biomedical applications [2], [3]. However, the use of Deep Learning in molecular communication, especially in the context of a physical testbed setup, is rare. Here, we will present an approach to demodulating transmissions within a molecular communication testbed [4] using a Convolutional Neural Network (CNN), a typical approach to Deep Learning. In contrast to conventional demodulation algorithms, very little analytical knowledge of the communication channel is necessary to train and apply a CNN. This could be especially useful in scenarios with changing channel parameters.

Some work on CNNs in molecular communication was presented in [5]–[7]. However, in all cases a model-based approach was chosen to generate training data. The trained predictors are not validated with physical experiments.

The authors of [8] generate experimental data in a testbed and use neural networks for a variety of detection algorithms. The achievable data rate is restricted to $2\,\mathrm{bit\,s^{-1}}$. However, due to transmission errors, the effective data rate is somewhat lower. In contrast to [8], we use a larger symbol alphabet with concentration shift keying (CSK) and reach an effective data rate of more than $5.5\,\mathrm{bit\,s^{-1}}$ for a remaining bit error rate of $1\,\%$.

II. Testbed

The used testbed consists of a transmitter (a micropump manufactured by Fraunhofer EMFT) [9], a tube (1.52 mm inner diameter) with an active background flow of water, driven by a peristaltic pump, and an inductive susceptibility sensor as the receiver [10]. Transmission is achieved through modulated injections ($0\,\mu\mathrm{L}$ to $30\,\mu\mathrm{L}$ injection volume) of magnetic nanoparticles, specifically superparamagnetic iron-oxide nanoparticles (SPIONs). An injected particle burst then travels with the laminar background flow to the sensor at a distance of 5 cm, where the particles are detected based on their magnetic properties. The inductive sensor is based on the LDC1612 (Texas Instruments) and uses a custom made detection coil (see [10] for further details).

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Different variations of CSK with 6 and 8 different amplitude values, as well as symbol rates of 1, 2 and 4 symbols per second are evaluated. A sufficiently large data set was recorded for each configuration (3626 symbols for 6 amplitude values, 4740 symbols for 8 amplitude values). As shown in [9], for CSK with 6 amplitude values, two symbols can be combined to encode 5 binary bits.

The signal measured at the receiver typically has a steep rising edge with a slow signal decay. This is due to the laminar flow profile in the channel, causing an axial distribution of the injected particle burst. An in-depth analysis of the channel response in the fundamental testbed system can be found in [11]. The change of susceptibility in a time step (rising edge in receivers signal) corresponds to the injected SPION volume.

III. Demodulation

Preprocessing is performed on the recorded signal before analysis. First, linear interpolation and a moving averaging filter are applied to mitigate timing deviations and background noise, respectively. Next, the signal is split into individual symbol intervals using the known symbol duration and significant rising edges, that are substantially steeper than the maximal change observed during no transmission, for synchronisation. The symbols are randomly split into a training set (80 %), a validation set (10 %) and a test set (10 %).

As a baseline reference we use a symbol detection algorithm based on linear discriminant analysis (LDA) with the three significant features; amplitude height, rising edge height and falling edge height. This concept was presented in [9].

In a novel approach to demodulating non-binary transmissions in molecular communication, we implemented a one-dimensional CNN with nine layers using the PyTorch[1] module for Python. An overview of the constructed CNN architecture is provided in Table I.

The pytorch function *CrossEntropyLoss* is used as the loss function. Adaptive Moment Estimation [12], with default values, is used for optimisation. Training is stopped once the validation loss has not decreased for 20 subsequent training epochs. Using an Nvidia GeForce RTX 2080, training is typically completed in under two minutes.

TABLE I: The constructed CNN architecture contains three convolutional layers (CONV), three max-pooling layers (MAX) and three fully-connected (FC) layers. DO denotes whether dropout ($p = 0.5$) is used. C is either 6 or 8, depending on the size of the used symbol alphabet.

Layer	Type	Input	Output	Kernel	Stride	DO
1	CONV	128×1	128×64	7	1	✗
2	MAX	128×64	64×64	2	2	✗
3	CONV	64×64	64×128	5	1	✗
4	MAX	64×128	32×128	2	2	✗
5	CONV	32×128	32×256	3	1	✗
6	MAX	32×256	16×256	2	2	✗
7	FC	16×256	1×4096	-	-	✓
8	FC	1×4096	1×4096	-	-	✓
9	FC	1×4096	$1 \times C$	-	-	✗

TABLE II: Comparison of classification accuracy, shown as a probability for a specific demodulation offset (i.e. misclassification syndrome), between LDA and CNN approach (zeros omitted). Results are similar for both algorithms at the lower symbol rates. A significant improvement is achieved using the new CNN classifier for a symbol rate of 4 Hz.

(a) Classification accuracy using 6 amplitude values.

	LDA			CNN		
Offset	**1 Hz**	**2 Hz**	**4 Hz**	**1 Hz**	**2 Hz**	**4 Hz**
0	0.90	0.99	0.53	0.93	0.99	0.65
1	0.10	0.01	0.26	0.06	0.01	0.15
2			0.11			0.09
3			0.03			0.05
4			0.04			0.03
5			0.03			0.04

(b) Classification accuracy using 8 amplitude values.

	LDA			CNN		
Offset	**1 Hz**	**2 Hz**	**4 Hz**	**1 Hz**	**2 Hz**	**4 Hz**
0	0.97	0.97	0.27	0.95	0.98	0.49
1	0.03	0.02	0.35	0.04	0.02	0.20
2			0.13			0.09
3			0.09			0.08
4			0.05			0.05
5			0.06			0.03
6			0.02			0.04
7			0.03			0.02

IV. Results and Discussion

At the lower symbol rates, 1 Hz and 2 Hz, the prediction performance of the CNN is good, with more than 90 % of symbols being classified correctly for both 6 and 8 amplitude values. The performance deteriorates (65 % correctly classified for 6 amplitude levels) at a symbol rate of 4 Hz due to a relative increase of timing errors. For the best configuration, 8 amplitude values with a symbol rate of 2 Hz, an effective data rate of $5.5\,\mathrm{bit\,s^{-1}}$ for a remaining bit error rate of 1 % is achievable, according to the noisy-channel coding theorem.

[1] https://pytorch.org

Table II shows a comparison between the classification performance of the conventional LDA approach and the designed CNN. The probabilities for the misclassification of a received symbol by a specific offset, as determined with the test set, are listed. For the lower symbol rates, both demodulation techniques perform similarly. However, the CNN significantly outperforms the LDA approach at a symbol rate of 4 Hz.

In conclusion, a CNN was, for the first time, successfully used to demodulate a CSK signal in a molecular communication setup. In comparison to a conventional LDA approach, a significantly better classification accuracy was achieved for higher symbol rates. Furthermore, less analytical knowledge of the received signal is necessary using the proposed CNN demodulation method. In future, we will investigate different CNN architectures and the implementation of a deep learning approach in the context of edge computing (such as with a field-programmable device).

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