Reviving Timing-based localization study

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May 26th 2020

Part 1. CCF analysis algorithm updating project
Part 2. Application of the machine learning approach

Part 1. Update CCF analysis algorithm

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May 26th 2020

Current localization problem

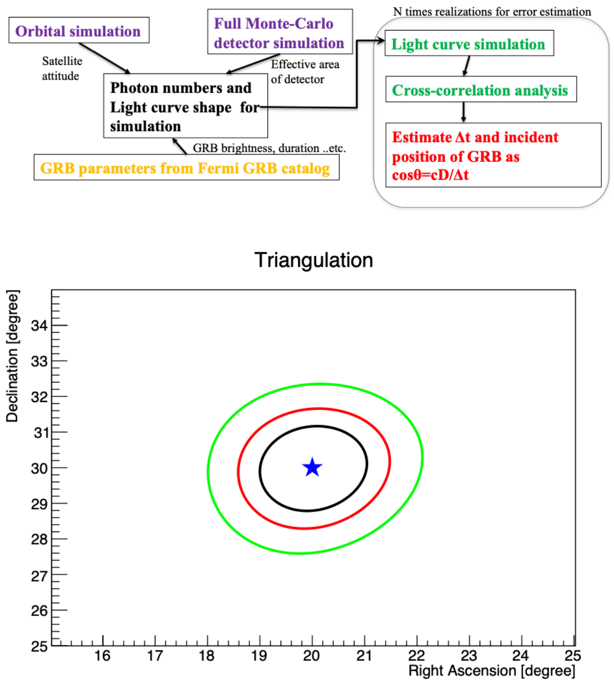
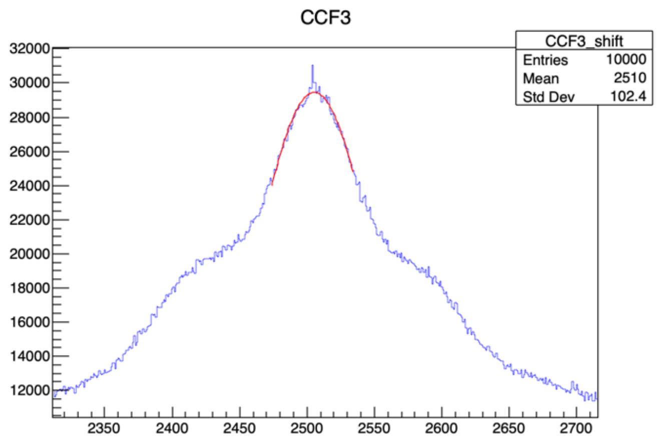
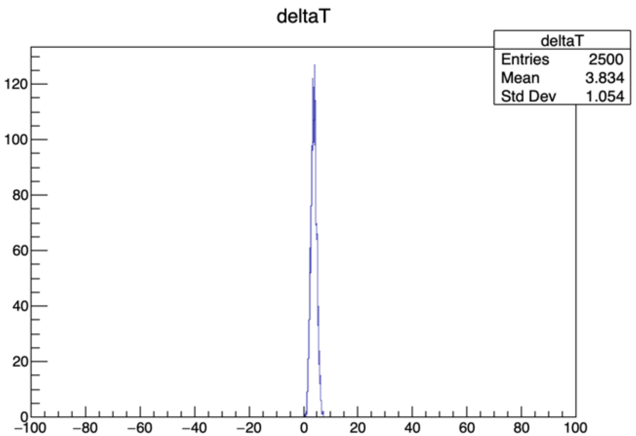


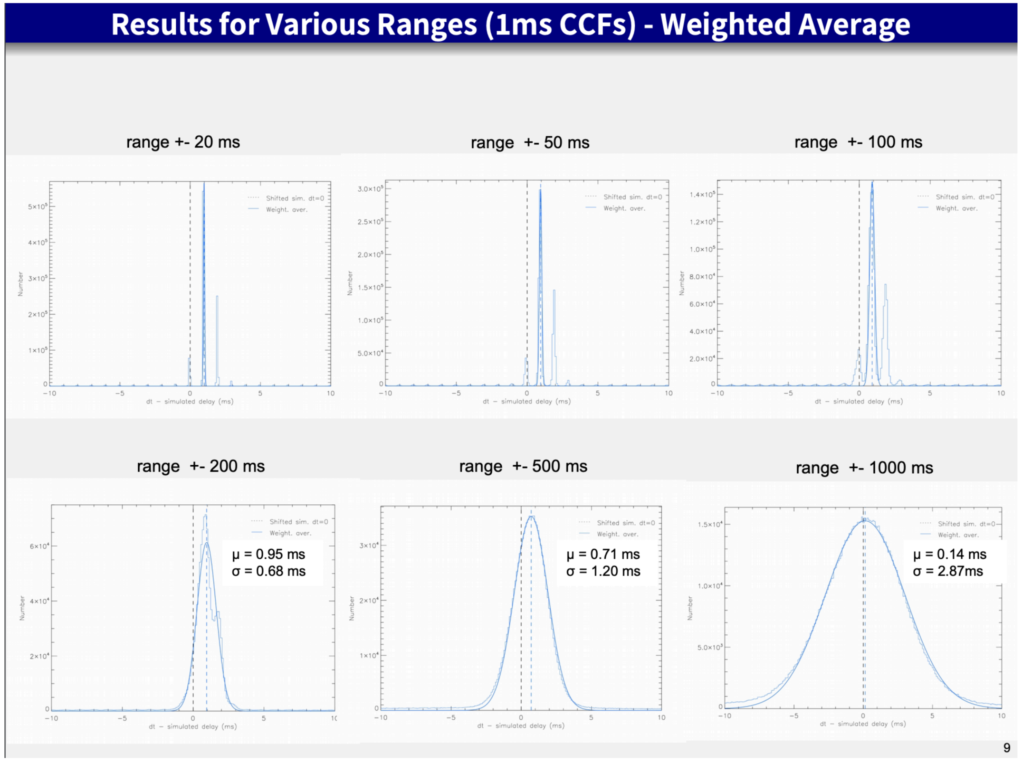
Fig. 2. top: a flow-chat of the localization simulation framework in this study. bottom: the example of the localization by using 9 satellites combination for the bright short GRB 090227772. A star marker shows the input position (R.A.=20, Dec=30 degree), and black, red and green contour is obtained confidence regions correspond to 1, 2 and 3 sigma significance.

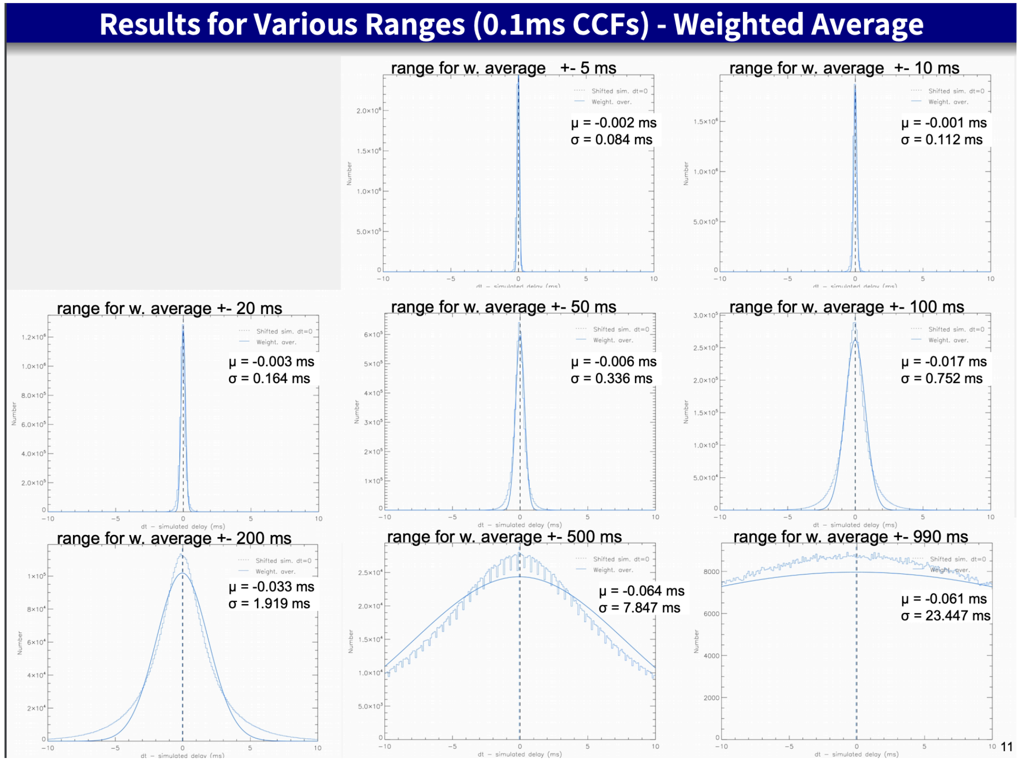




- ✓ Current localization uncertainty is mainly caused by the uncertainty of the estimated time-difference (delta-t)
- ✓ The CCF peak is obtained by the gaussian function fitting around the CCF maximum
- ✓ Delta-t uncertainty is limited to be ~1ms even for the brightest short GRB ➔ current best localization error is still ~ 1deg
- ✓ Human-eyes verification is mandatory for such fitting procedures
- ✓ Other better algorithm to determine the CCF peak ?

Gaussian fitting vs weighted mean

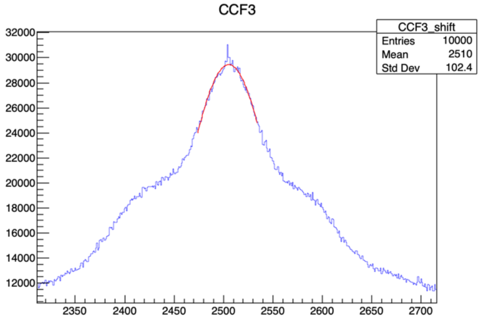




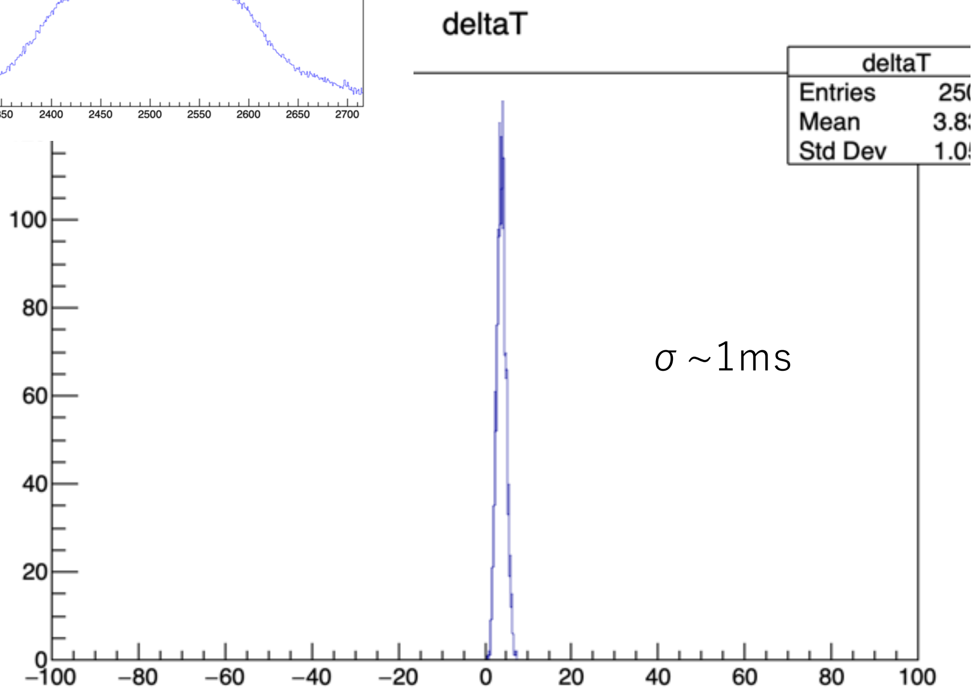
From Jakub-san's analysis, weighted mean could have < 1ms delta-t uncertainty (1-sigma), let's check it !

Analysis samples

- Only one bright short GRB090227772 is tested
- 2500 simulations with a fixed given delta-t (4ms)
- 1 ms time resolution is checked so far
- Peak is estimated by (excluding artificial one-bin spike)
  - gaussian fitting around the maximum bin (+/-30ms)
  - weighted mean around the maximum bin (+/-30ms)
- The maximum bin is estimated by
  - a simple maximum bin by the original CCF
  - a maximum bin excluding artificial one-bin spike



Gaussian fitting

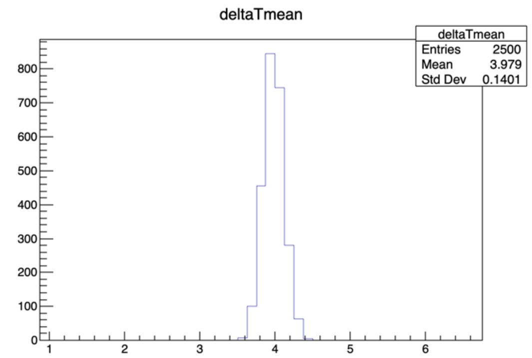


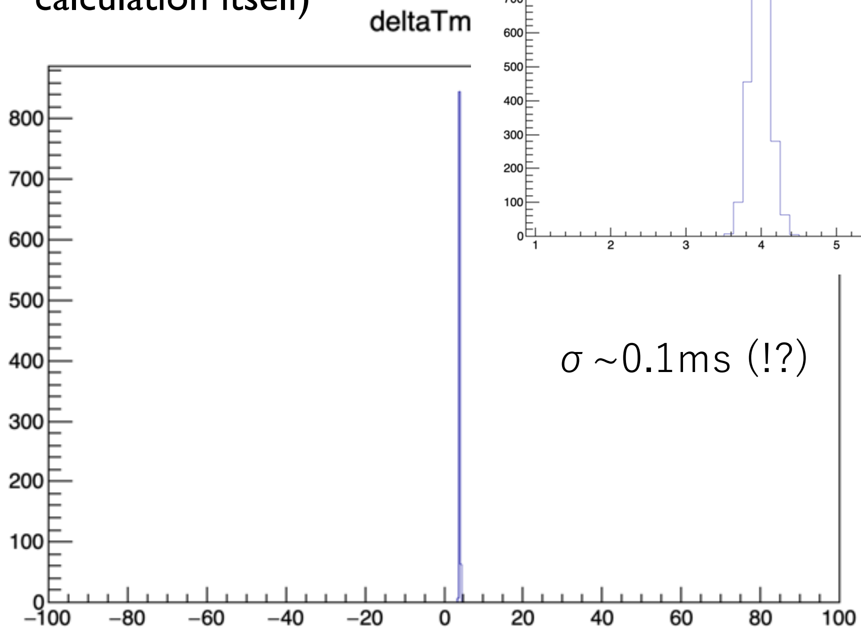
σ ~1ms

Delta-T

Weighted Av. around
"simple" maximum bin
== "Fixed calculation center"
(strong spike is excluded
from weighted average
calculation itself)

Zoom



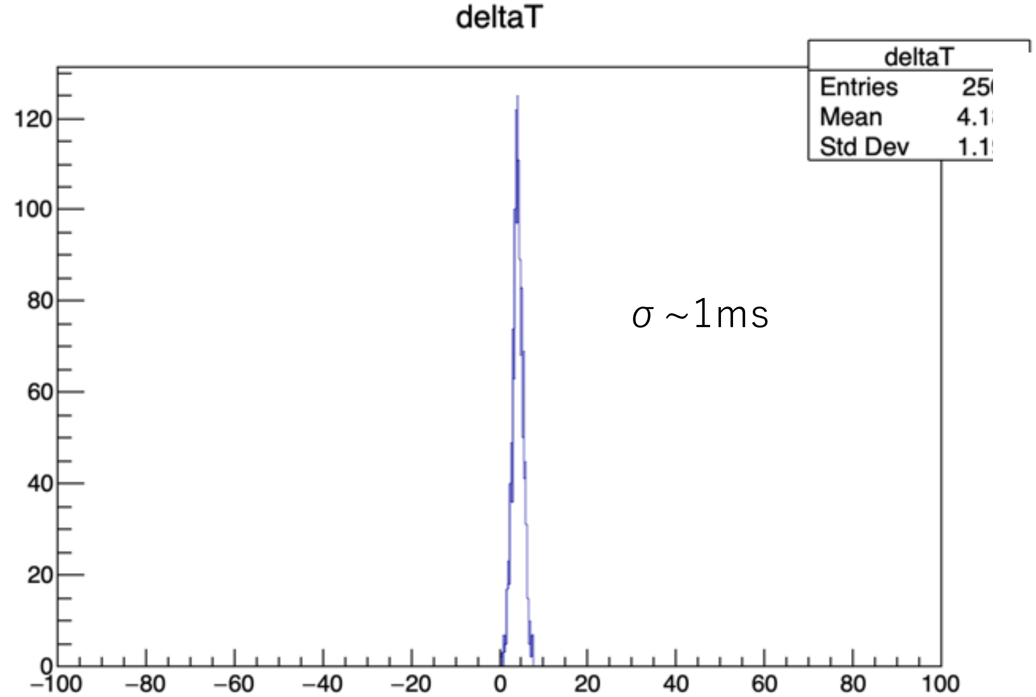


σ ~0.1ms (!?)

Delta-T

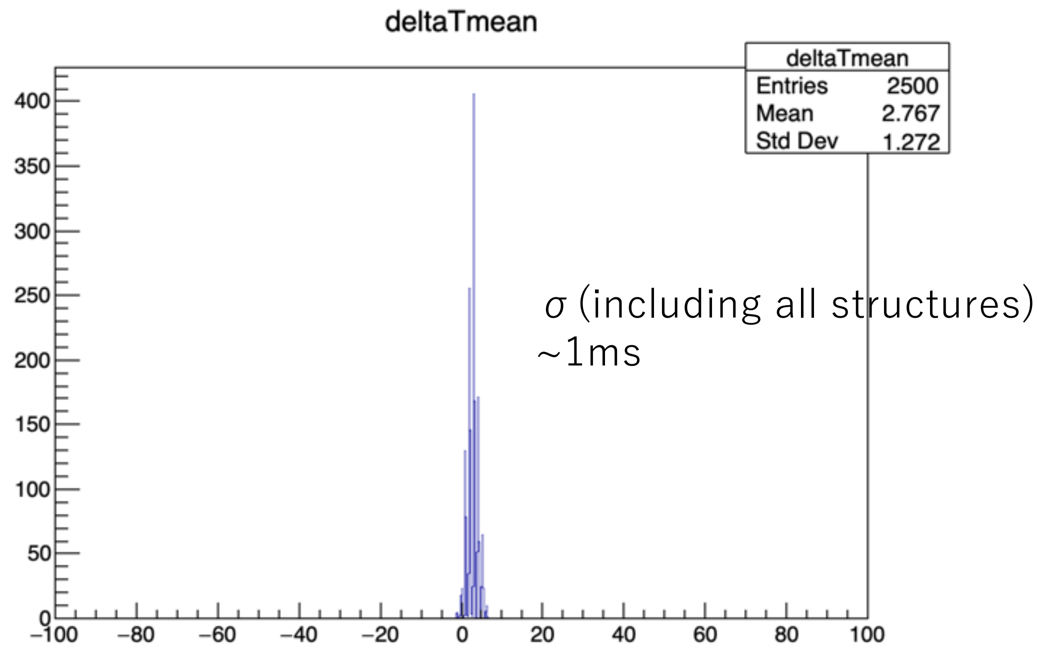
Analysis range : +/-30ms (typical minimum variability timescale Bhat+13)

Gaussian fitting



Delta-T

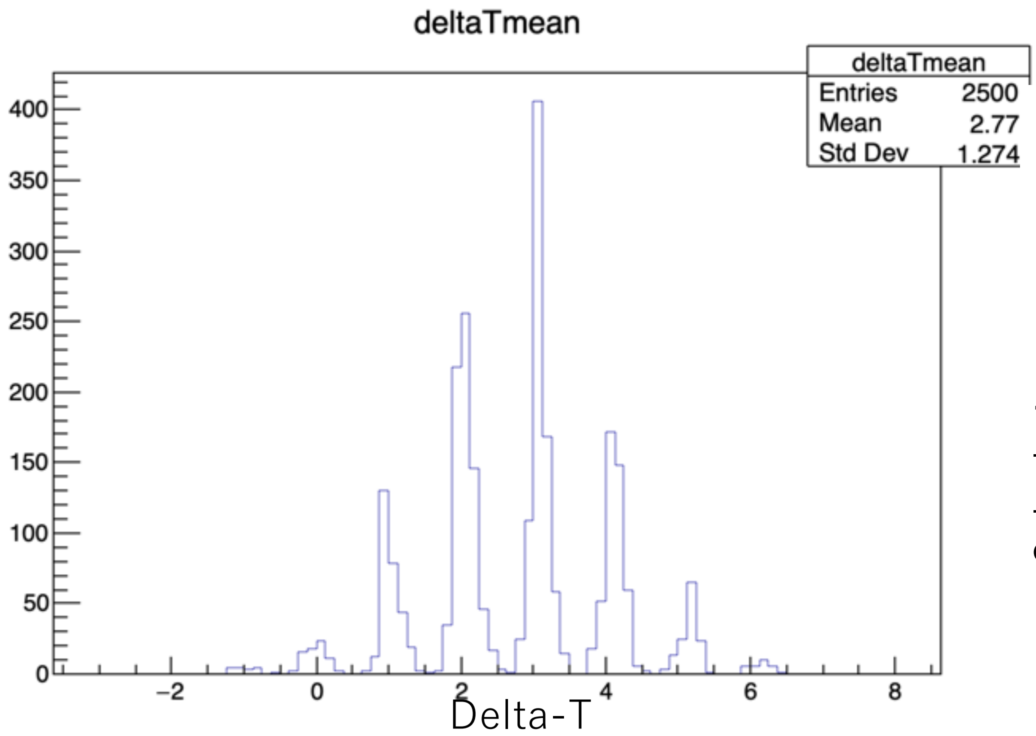
Weighted Av. The maximum bin is estimated exclude the strong spike bin



Delta-T

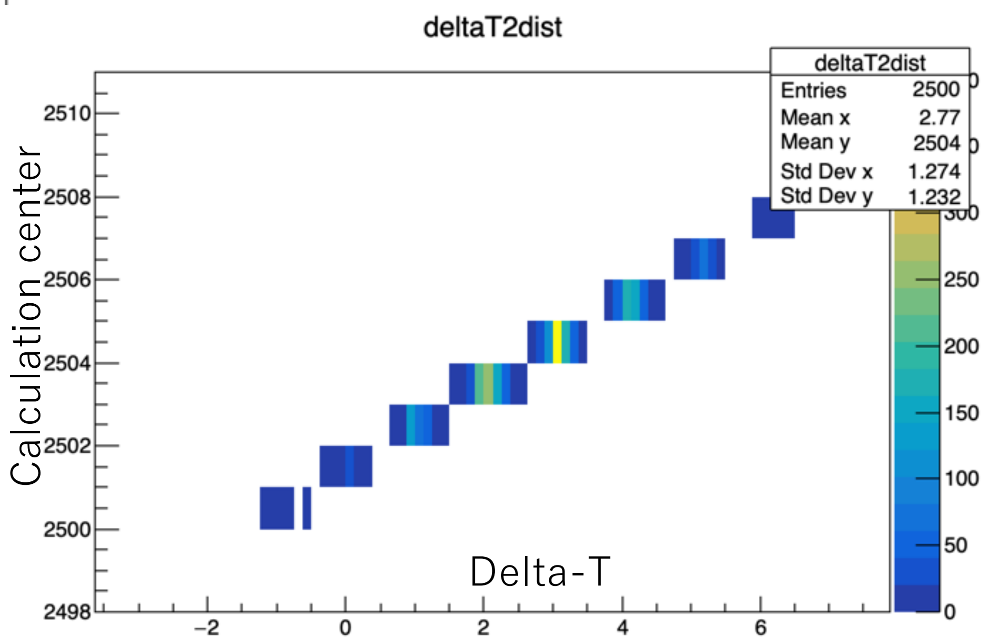
Analysis range : +/-30ms (typical minimum variability timescale Bhat+13)

Zoomed up: Weighted Av. The maximum bin is estimated exclude the strong spike bin



Each sub-structure shows similar shape to the "fixed calculation center" case.
Including sub-structure, entire width of distribution is similar to the gaussian fitting case

To be continued this work
- use 0.1 ms LC
- iterative process to determine the analysis center



Each sub-structure belong to the different calculation center

Timing based localization by the machine learning approach

M. Ohno, Y. Ichinohe, R. Jakub, and N. Werner

May 26th, 2020 v0: simple time delay estimation

Motivation

- CCF based time-delay analysis is a standard way for the timing-based localization
- Problem for the CCF analysis are

1) variation of the CCF shape makes the framework automated difficult (need human-eyes analysis and validation)

2) current gaussian fitting approach limits the accuracy ~1ms (corresponds to ~1 deg localization error)

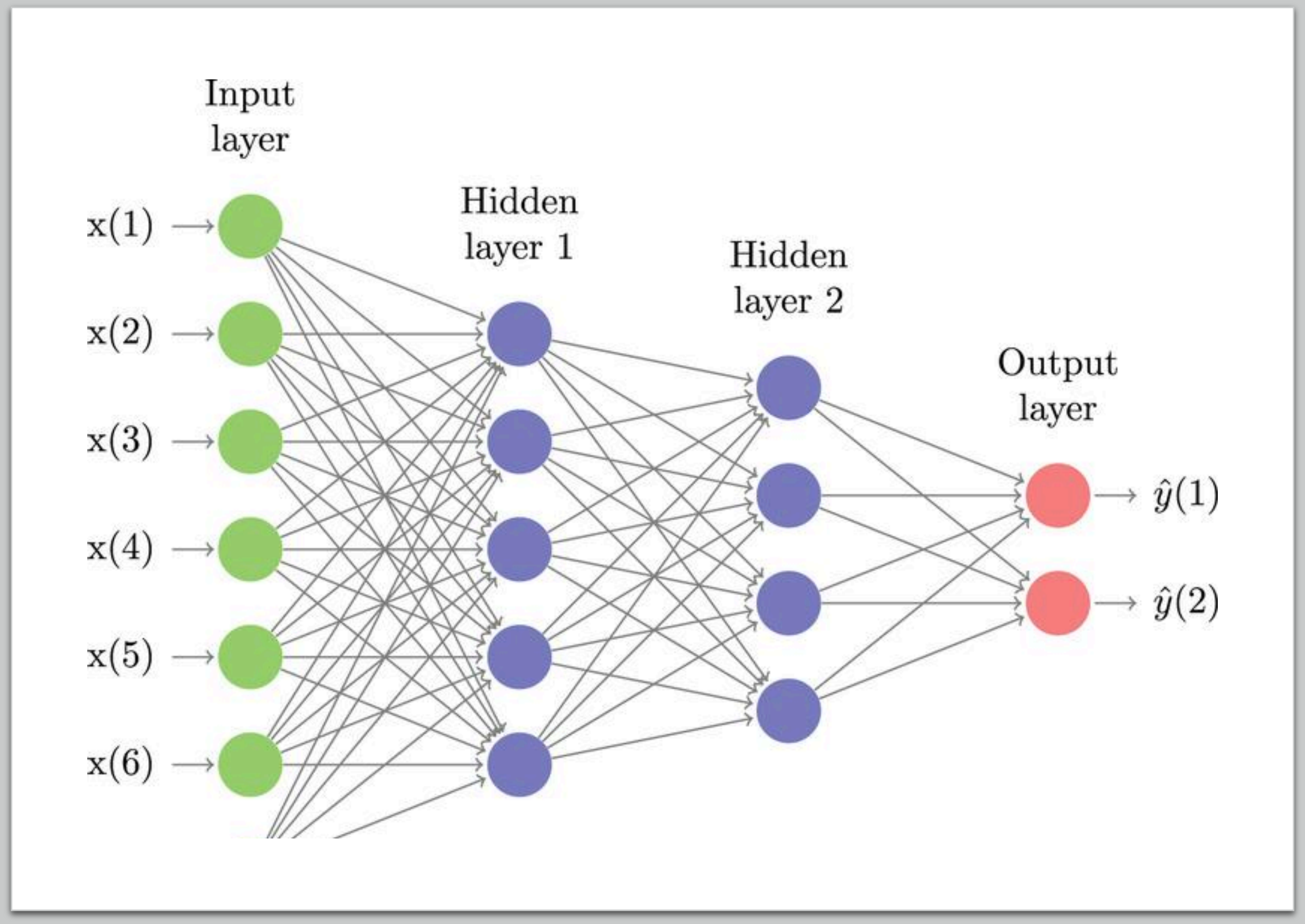
- Machine learning approach ?

  - helpful to automation ?
  - any possibilities to improve the time-delay estimation ?

Goal of the concept

input layer = light curve from multiple satellites

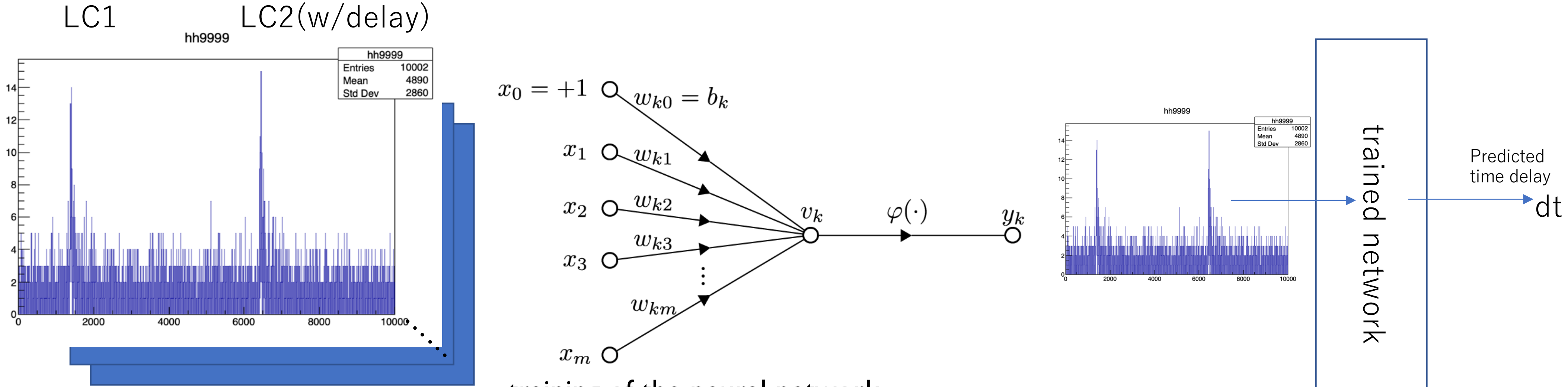
output layer = parameter vector that we want to know (RA, Dec, flux .. Etc.)



Is this concept realistic ? Let's start from a simple estimation !

A simple time-delay estimation

- Input layer : two light curves with a give time delay (1-D vector)
  simulated from the same light curve (GRB090227772)
- Output layer : predicted time delay
- training : large number sets of two light curves with a random time delay (-50ms to +50ms)



training of the neural network
(weight/activation function)

Tensorflow as a Keras backend

- Tensorfow : open source library for the deep learning
- Keras : python based open source neural network library for quick experiment of the deep neural network learning which supports Tensorflow as the backend
- I need more "deep learning" to explain what those framework are, and how they are working !

```
model=Sequential()
model.add(Dense(units=48, input_shape=(orig_dim,),activation='sigmoid'))
model.add(Dense(units=24,activation='sigmoid'))
model.add(Dense(units=1))
```

Define sequential hidden layers with activation function

```
model.compile(loss='mean_squared_error', optimizer='sgd')
```

Define how to optimize the parameters (loss function, optimizer sgd: stochastic gradient decent)

```
history=model.fit(xtrain,ytrain,epochs=nepochs,batch_size=30,validation_data=(xvalid,yvalid))
```

Run training using xtrain (light curve) and ytrain (answer:dt) with some iteration parameters (ephocs)

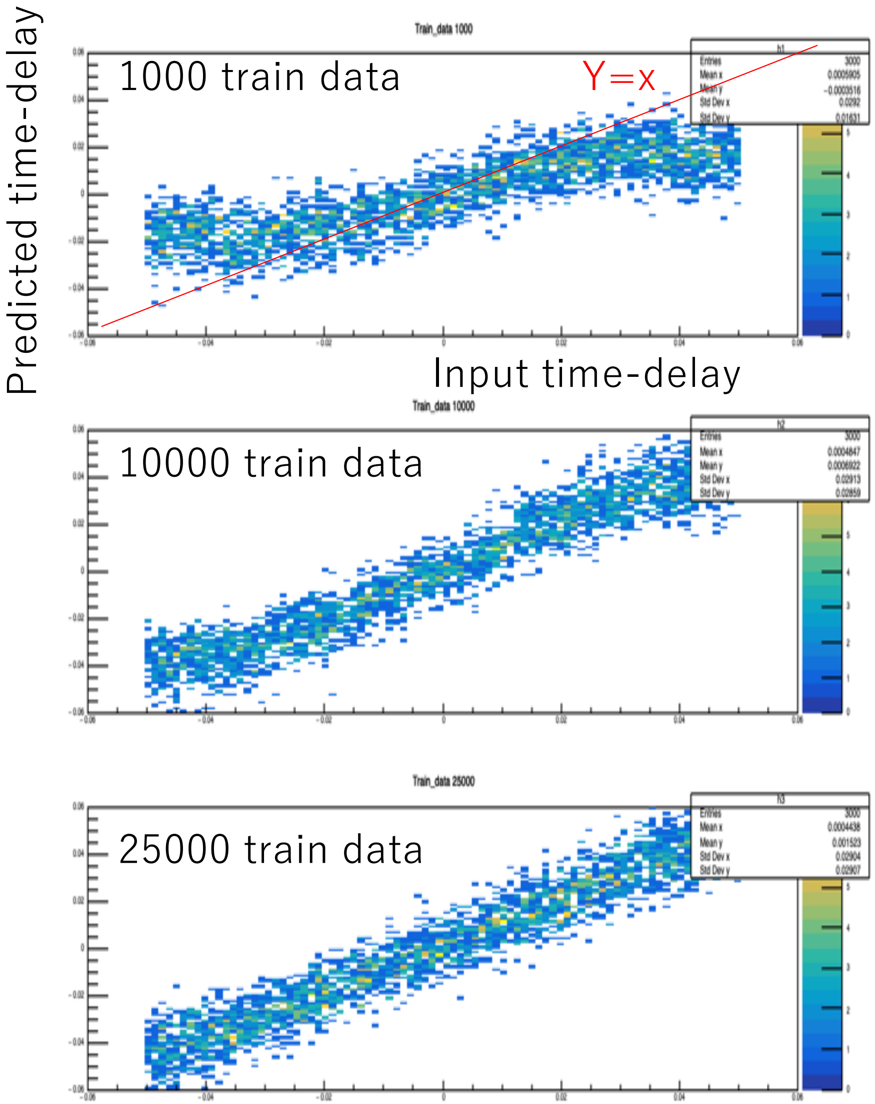
Training the network !

```
ターミナル — -tcsh — Basic — ⌥⌘2
8d20 initialized for platform Host (this does not guarantee that XLA will be used). Devices:
2020-05-26 02:20:26.265088: I tensorflow/compiler/xla/service/service.cc:176]   StreamExecutor devic
e (0): Host, Default Version
Train on 5000 samples, validate on 3000 samples
Epoch 1/50
5000/5000 [==============================] - 1s 125us/step - loss: 0.0067 - val_loss: 8.4776e-04
Epoch 2/50
5000/5000 [==============================] - 0s 97us/step - loss: 8.6877e-04 - val_loss: 7.9108e-04
Epoch 3/50
5000/5000 [==============================] - 0s 98us/step - loss: 8.0999e-04 - val_loss: 7.4528e-04
Epoch 4/50
5000/5000 [==============================] - 0s 97us/step - loss: 7.5696e-04 - val_loss: 6.8836e-04
Epoch 5/50
5000/5000 [==============================] - 0s 96us/step - loss: 7.0569e-04 - val_loss: 6.4489e-04
Epoch 6/50
5000/5000 [==============================] - 0s 97us/step - loss: 6.6064e-04 - val_loss: 6.1185e-04
Epoch 7/50
5000/5000 [==============================] - 0s 95us/step - loss: 6.1716e-04 - val_loss: 5.6381e-04
Epoch 8/50
5000/5000 [==============================] - 0s 99us/step - loss: 5.7875e-04 - val_loss: 5.3748e-04
Epoch 9/50
5000/5000 [==============================] - 0s 97us/step - loss: 5.4333e-04 - val_loss: 4.9581e-04
Epoch 10/50
5000/5000 [==============================] - 0s 96us/step - loss: 5.0910e-04 - val_loss: 4.6584e-04
Epoch 11/50
5000/5000 [==============================] - 0s 96us/step - loss: 4.7810e-04 - val_loss: 4.3833e-04
Epoch 12/50
5000/5000 [==============================] - 0s 96us/step - loss: 4.4944e-04 - val_loss: 4.1285e-04
Epoch 13/50
5000/5000 [==============================] - 0s 97us/step - loss: 4.2409e-04 - val_loss: 3.8886e-04
Epoch 14/50
5000/5000 [==============================] - 0s 96us/step - loss: 4.0019e-04 - val_loss: 3.6735e-04
Epoch 15/50
5000/5000 [==============================] - 0s 97us/step - loss: 3.7705e-04 - val_loss: 3.4700e-04
Epoch 16/50
```

Training data : 5000 set
Iterative number : 50 epochs

The loss function estimate value decreasing
➔ Closer to the input value

Here, various parameters are investigated
- Amount of the training data
- Amount of the iterative sequence
- time-resolution of the input data



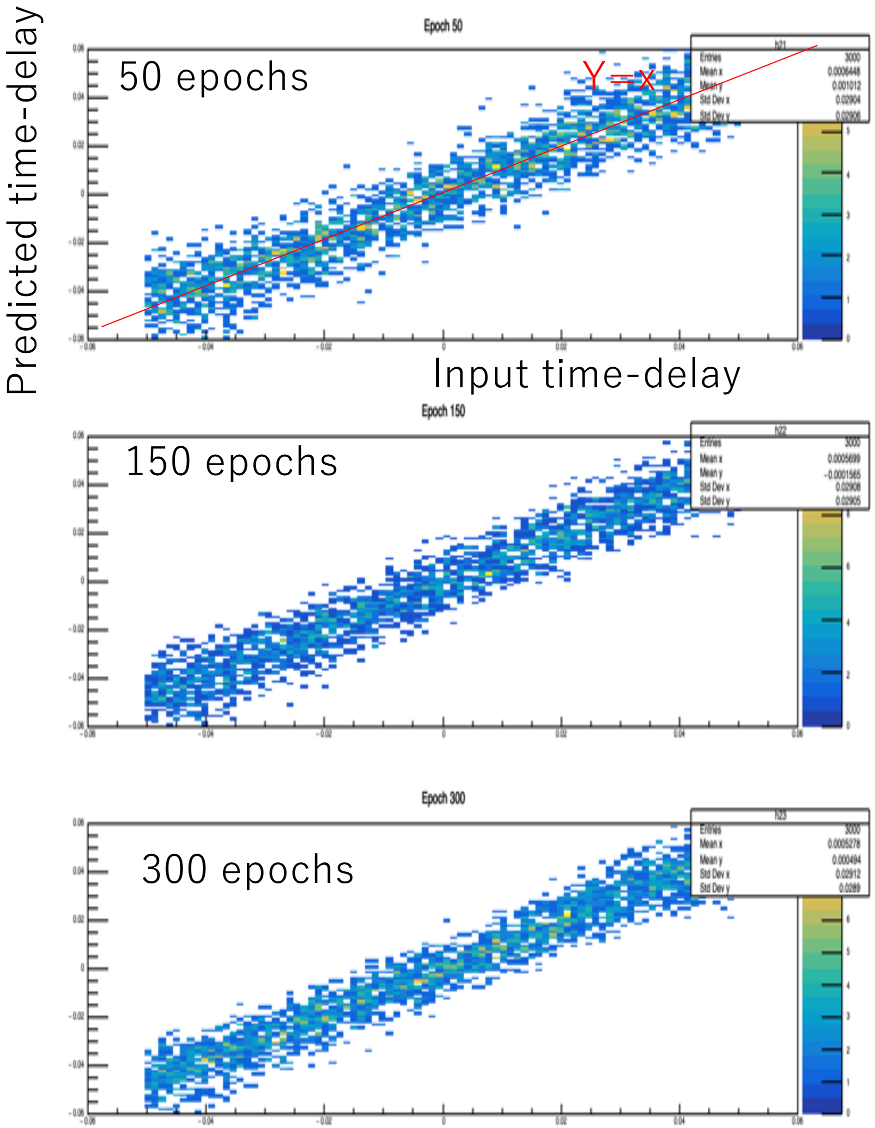
Results 1: train data set dependency

- Input light curve : 1 ms resolution
- Iterative number is fixed to be 100

- Systematic deviation is seen for the smaller train data result

- 25000 train data gives almost straight result

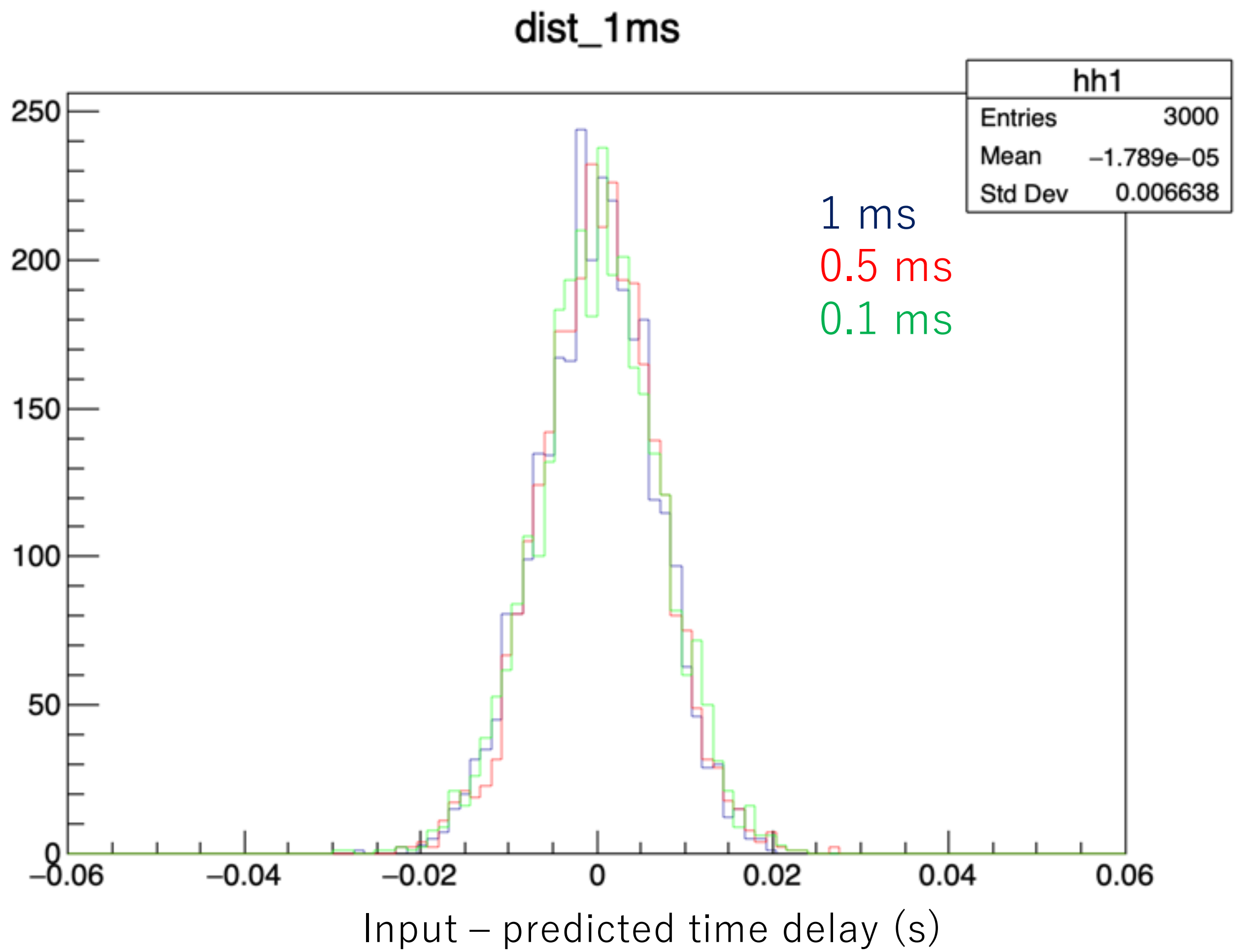
Result2: iterative number dependency



- Input light curve : 1 ms resolution
- Train data number is fixed to be 25000

- Larger iteration gives a narrower distribution (higher accuracy !)

Result 3 : time-resolution and current deltaT estimation uncertainty



- Iterative number is fixed to be 300
- Train data number is fixed to be 25000

- Accuracy of the predicted time delay does NOT depend on the time-resolution of the input light curve, interesting…

- Current delta-t estimation uncertainty is ~6 ms, which is still much worse than the CCF approach (~1ms)

- Further investigation of the training approach could improve the result ? Under discussion with Yuto !