Energy and timing resolution boost with waveform analysis

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I. Motivation

In a neutrino or dark matter experiment, to improve **energy and timing resolution** with waveform analysis,

waveform $\boldsymbol{w}$ from PMTs in LS detector	→ analysis →	PE count expectation μ event time t_0 *high resolution needed*

FSMP is a *reliable* analysis method in **Bayesian** sense. It deals with *pile-ups*, and gives better resolution of μ and t_0.

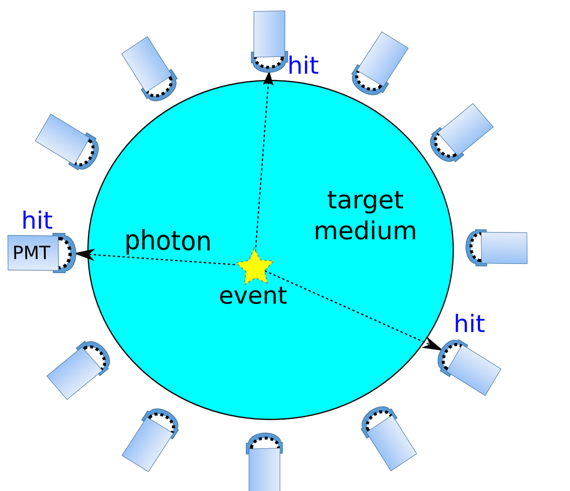

Fig. 1: Sketch of an liquid scintillator detector, such as JNE, JUNO, KamLAND, Borexino.

II. Bayesian waveform analysis

$$p(\boldsymbol{z}, t_0|\boldsymbol{w}) = \frac{p(\boldsymbol{w}|\boldsymbol{z}, t_0)p(\boldsymbol{z}, t_0)}{p(\boldsymbol{w})}$$

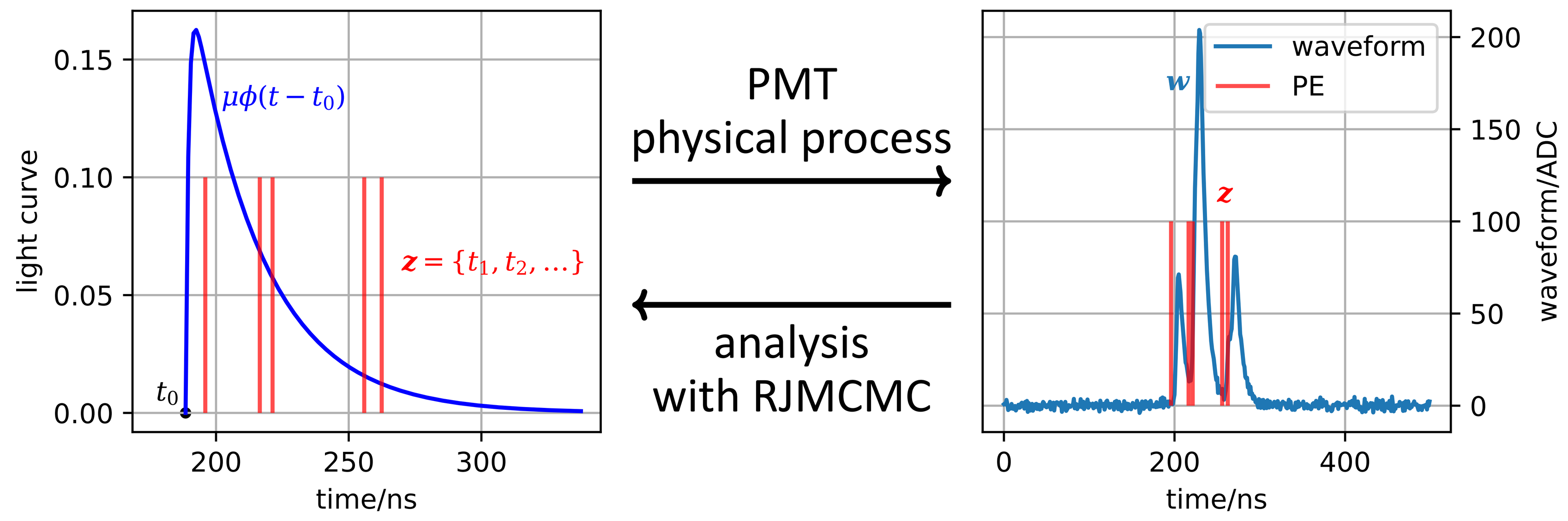

Fig. 2: Sample PEs from Poisson process

Fig. 3: Convolve PEs into a waveform

The event energy E and position $\boldsymbol{r}$ may be estimated by MLE:

$$(\hat{E}, \hat{\boldsymbol{r}}) = \arg\max_{E,\boldsymbol{r}} p(E, \boldsymbol{r}|\mu, t_0, \boldsymbol{w}) = \arg\max_{E,\boldsymbol{r}} \frac{p(\mu, t_0|E, \boldsymbol{r})p(E, \boldsymbol{r})}{p(\mu, t_0|\boldsymbol{w})}$$

III. Charge model for MCP-PMTs

There are two kinds of PE in MCP-PMTs (arXiv 2402.13266) [1]. We use a mixture of multiple normal distributions to represent the charge model.

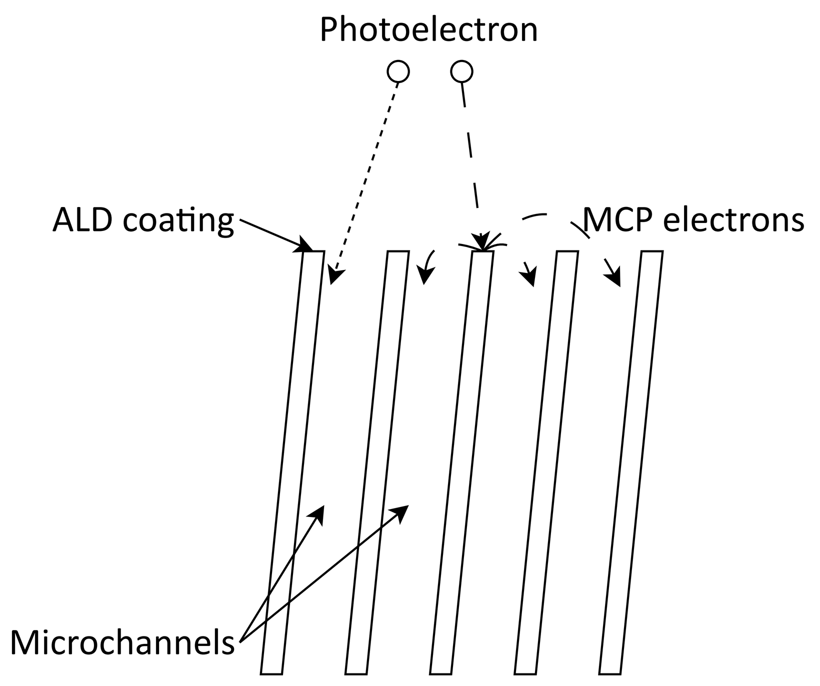

Fig. 4: A sketch of MCP and MCPes. A PE may go through the microchannel, or hit on the ALD coated surface.

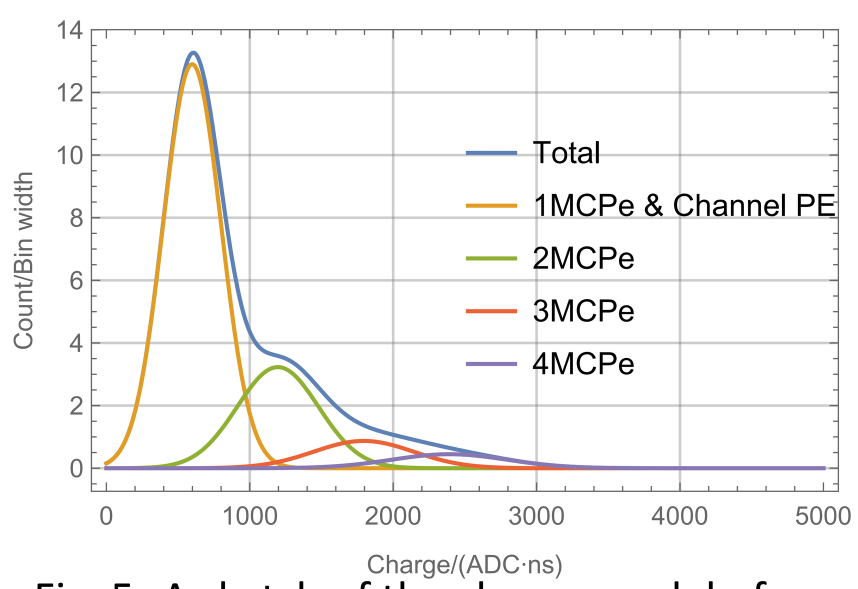

Fig. 5: A sketch of the charge model of an MCP-PMT. The vertical axis represents the number of waveforms.

IV. The MCMC steps in FSMP

Fast stochastic matching pursuit (FSMP, arXiv 2403.03156) [2, 3] supports any charge model constructed with multiple normal distributions, including MCP-PMTs' charge model.

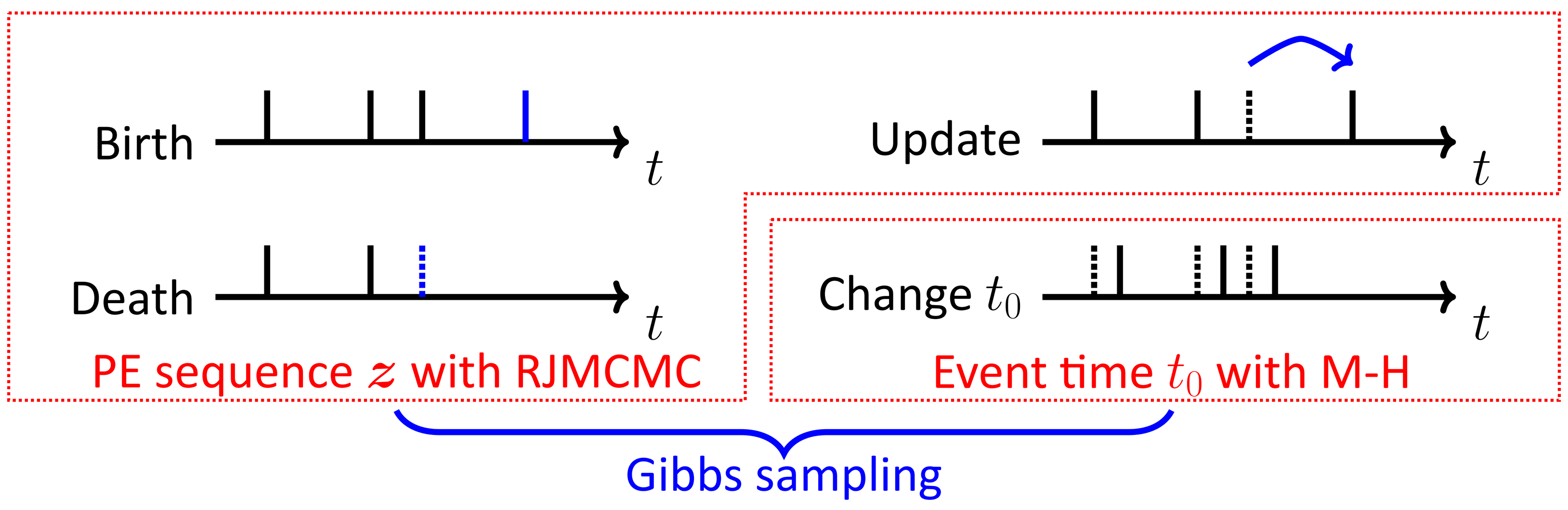

Fig. 6: The sketch of jumps of z and sampling t_0. The RJMCMC and Metropolis-Hastings samplers are mixed with the Gibbs sampling.

V. Bias and resolution

The relative resolution of μ, and the resolution of t_0 are defined as

$$\eta' = \frac{\sqrt{\mathrm{Var}[\hat{\mu}]}/\,\mathrm{E}[\hat{\mu}]}{\sqrt{\mathrm{Var}[N_\mathrm{PE}]}/\,\mathrm{E}[N_\mathrm{PE}]}, \eta_t = \frac{\sqrt{\mathrm{Var}[\hat{t}_0 - t_0]}}{E[\hat{t}_0]}$$

where N_PE is number of PEs. In the **most optimistic** case, the resolution improvement of μ could be seen as the improvement of energy resolution.

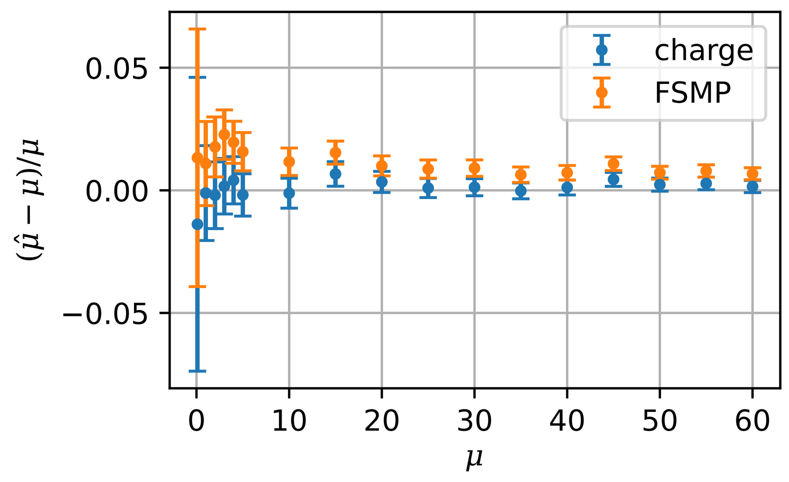

Fig. 7: The relative bias of $\hat{\mu}$.

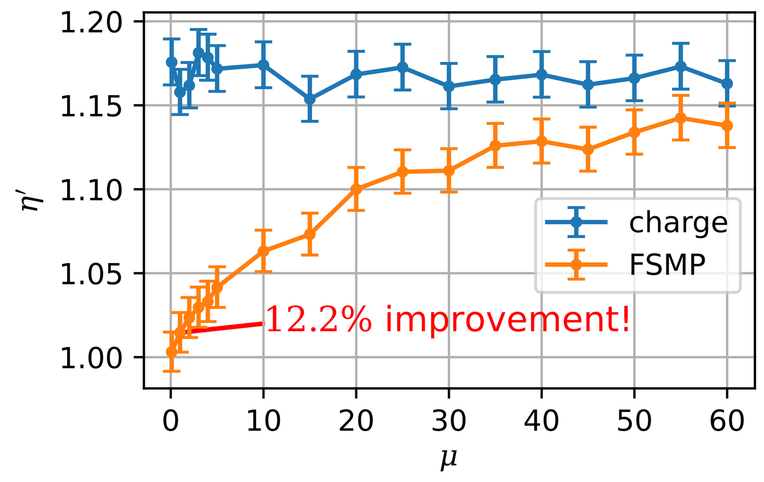

Fig. 8: The relative resolution of $\hat{\mu}$.

The charge method is the integration of waveforms.

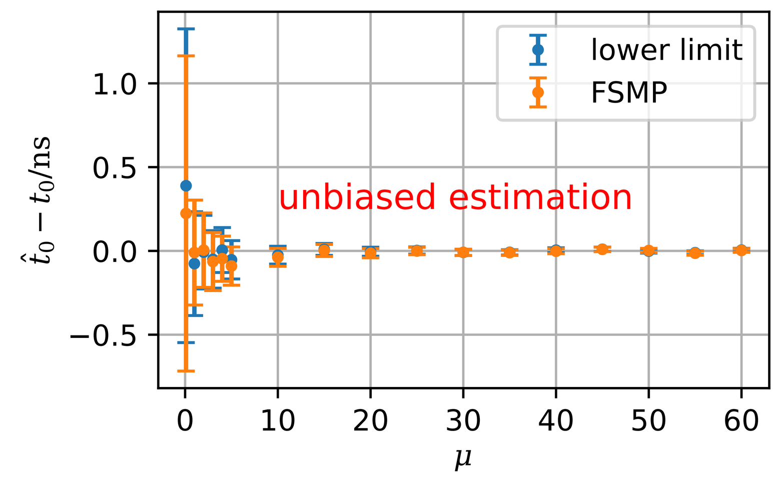

Fig. 9: The bias of $\hat{t}_0$.

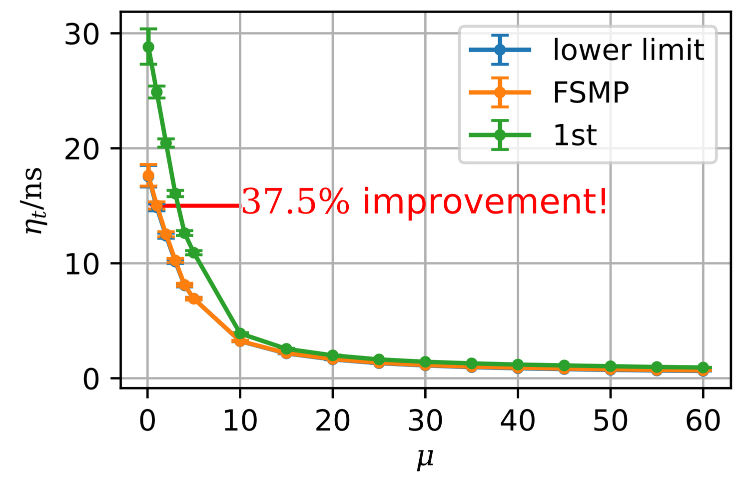

Fig. 10: The resolution of $\hat{t}_0$.

The lower limit method is M-H sampling with true PE sequence; the 1st method uses the first PE time as event time, which is biased.

VI. GPU acceleration

FSMP is accelerated with batched algorithm on GPU: a lot of waveforms are operated together, instead of analyzing them one by one.

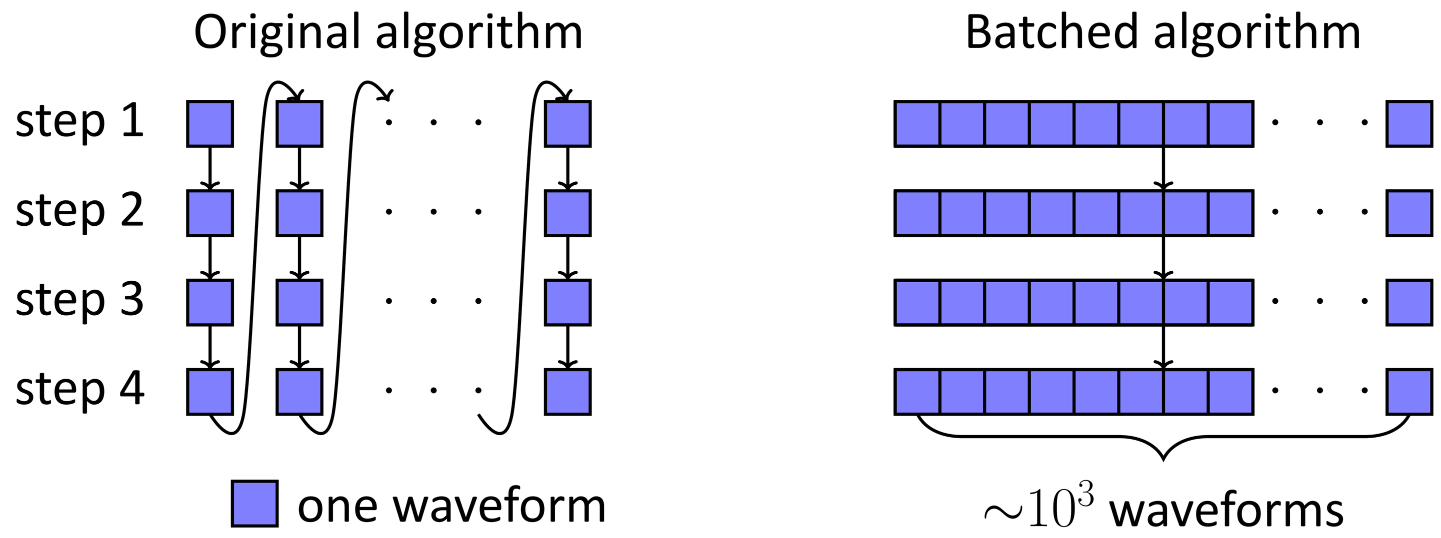

Fig. 11: A sketch of the original and the batched algorithm.

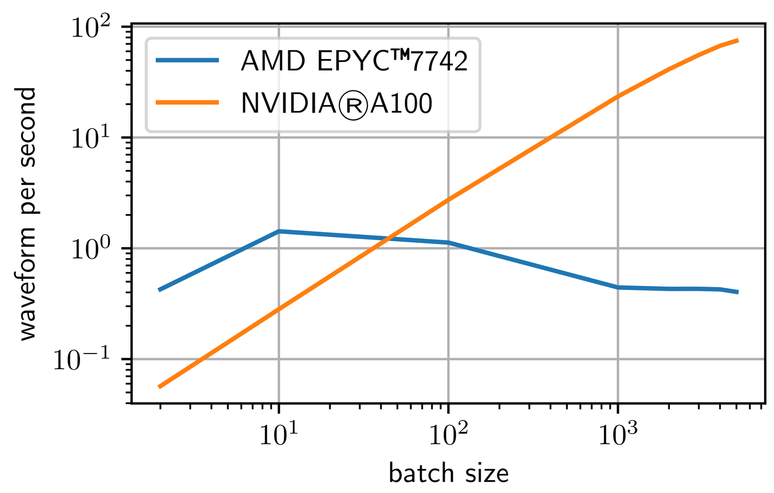

Fig. 12: The batched method performs ~ 100 waveforms per second with batch size $\sim 10^3$ on NVIDIA®A100, and it is faster than original algorithm on CPU by more than 2 orders of magnitude.

VII. Summary

- **Better energy resolution:** up to $(12.2 \pm 1.4)\,\%$ better ($\mu = 1$).
- **Better timing resolution:** unbiased, $(37.5 \pm 1.8)\,\%$ better ($\mu = 1$).
- **High performance:** ~ 100 waveforms per second, ~ 1000 times faster on consumer GPUs than CPUs.

References

[1] Jun Weng et al., 2024, arXiv:2402.13266.

[2] Dacheng Xu et al. *Journal of Instrumentation*, 6 2022, arXiv:2112.06913.

[3] Yuyi Wang et al., 2024, arXiv:2403.03156.