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機械学習を用いた ISS ソーレ係数測定実験の干渉縞位相解析・接続

Phase Analysis-Unwrapping using Machine Learning for Interference Fringe in Soret Coefficient Measurements on ISS

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1. Introduction

A laser interferometer enables contactless measurements of very fine temperature changes in a solution as the phase change $\Delta\phi$ of observed interference fringes, which was used for the Soret coefficient measurement on ISS. Intensity time series of the fringes $I(t)$ are processed through phase analysis-unwrapping procedures[1)–3)] to determine $\Delta\phi$. However, analysis formulas and parameters during the existing rule-based procedures depend on the optical set-up and fringe conditions, which disturbs the measurement versatility. Machine learning, in which training intensity-time relations faithfully simulating the observed ones is critical, is expected to replace the rule-based procedures. We then proposed the phase analysis-unwrapping procedure applied machine learning with artificial intensity time series generated as follows: generating ideal time series and processing them, such as scaling, to simulate the observed one. The objective of this study is to reveal whether the analysis accuracy of the proposed procedure can achieve the existing rule-based one. We evaluated the accuracy of the proposed procedure with processed and non-processed artificial data.

2. Procedures of generating training data and machine learning

Figure 1 shows the schematics of evaluation processes in this study. The values of X and t indicate the vertical position and holding time, respectively. The temperature changes in a homogeneous solution and glass given temperature difference were numerically calculated as $\Delta T(X,t)_{\mathrm{art,s}}$ and $\Delta T(X,t)_{\mathrm{art,g}}$, respectively, **(b)** to simulate ones (Run #1-09 in *Soret-Facet* Mission) measured using the interferometer on ISS [3)] **(a)**. The phase changes $\Delta\phi(X,t)_{\mathrm{art,s}}$ and $\Delta\phi(X,t)_{\mathrm{art,g}}$ were obtained by substituting $\Delta T(X,t)_{\mathrm{art,s}}$ and $\Delta T(X,t)_{\mathrm{art,g}}$ into the refractive index-phase formula about temperature, respectively **(c)**. The phase change $\Delta\phi(X,t)_{\mathrm{art}}$, which reproduces one observed as the sum of solution and glass ones, was obtained as $\Delta\phi(X,t)_{\mathrm{art}} = \Delta\phi(X,t)_{\mathrm{art,s}} + \Delta\phi(X,t)_{\mathrm{art,g}} \times 12/13 + \theta(X)$: $\theta(X)$ consists of spatially linearly increasing phase values **(d)**. The artificial intensity time series $I(X,t)_{\mathrm{art}}$ was obtained by substituting $\Delta\phi(X,t)_{\mathrm{art}}$ into the phase-intensity formula **(e)**. The values of $\Delta\phi(X,t)_{\mathrm{art}}$ and $I(X,t)_{\mathrm{art}}$ were simultaneously processed through following processes to complement the differences (F1) to (F4) described in Sec. **3**: adding a phase to $\Delta\phi(X,t)_{\mathrm{art}}$ (phase shifting) **(f1)**, reducing $I(X,t)_{\mathrm{art}}$ amplitudes to the averaged $I(X,t)_{\mathrm{exp}}$ ones (scaling) **(f2)**, adding random intensities to $I(X,t)_{\mathrm{art}}$ (noising) **(f3)**, and shifting the time of $I(X,t)_{\mathrm{art}}$ (temporal shifting) **(f4)**. The gradient boosting method was applied to the processed, or non-processed, $I(X,t)_{\mathrm{art}}$ and the corresponding phase change $\Delta\phi_{art} = \Delta\phi(X,900)_{art} - \Delta\phi(X,0)_{art}$ to obtain regression trees which assign $\Delta\phi$ according to the intensity-time relations **(g1)** and **(g2)**. The phase changes were predicted as $\Delta\phi_{pred}$ by inputting $I(X,t)_{exp}$ into the regression trees **(h1)** and **(h2)**. The experimental phase changes $\Delta\phi_{exp}$ were also obtained for comparison using the existing rule-based procedures [2), 3)] **(i)**.

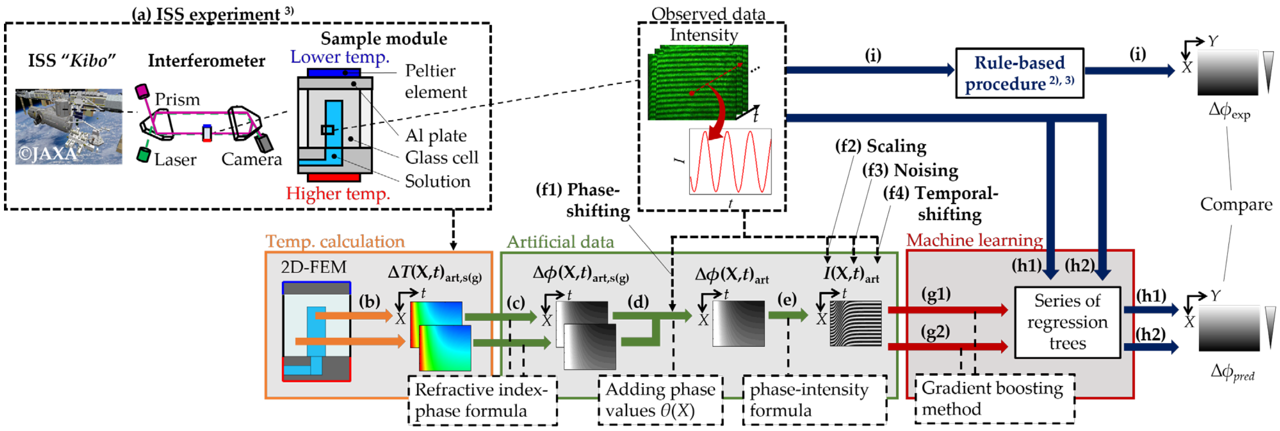

Fig. 1 Schematics of evaluation processes in this study. The alphabets correspond to ones in Sec. **2**.

3. Results

The values of $\Delta\phi_{art}$ were larger than $\Delta\phi_{exp}$ while $\Delta T(X,t)_{art,s}$ were almost the same as the experimental results measured using thermocouples. The following features were confirmed in $I(X,t)_{exp}$ while they were not in the non-processed $I(X,t)_{art}$: initial value changes due to fringe distortions (F1), amplitude changes due to laser intensity distribution (F2), and noise due to air fluctuations (F3). The peak positions of $I(X,t)_{exp}$ and $I(X,t)_{art}$ were shifted by several frames (F4). The values of $\Delta\phi_{pred}$ with spatial gradient as confirmed in $\Delta\phi_{exp}$ were obtained using processed training data. In contrast, the values of $\Delta\phi_{pred}$ with the non-processed training data were spatially almost constant.

4. Discussion

The averaged root mean square errors (RMSE) of $\Delta\phi_{pred}$ and $\Delta\phi_{exp}$ were calculated against the robust regressed $\Delta\phi_{exp}$. As a result, RMSE for $\Delta\phi_{exp}$ and processed $\Delta\phi_{pred}$ were about 2 and non-processed $\Delta\phi_{pred}$ was about 4, respectively. The averaged determination coefficient R^2 for $\Delta\phi_{exp}$ and processed $\Delta\phi_{pred}$ were about 0.8 and non-processed $\Delta\phi_{pred}$ was about 0.1, respectively. These results revealed that the proposed process improves the analysis accuracy of the machine learning applied phase analysis-unwrapping procedure and can achieve almost the same accuracy, at least on average, as the existing rule-based ones with relatively large outliers. The average and minimum errors of $\Delta\phi_{exp}$ and $\Delta\phi_{pred}$ gradients with robust regressions, which reduce effects of outliers, were about 30% and less than 10%, respectively. The result revealed that the machine learning applied procedure can achieve almost the same accuracy as the existing one regardless of outliers.

5. Conclusion

The following was revealed through applying machine learning to the proposed and non-processed artificial intensity time series. A machine learning applied phase analysis-unwrapping procedure trained on numerically calculated artificial intensity time series, in which the following processes are simultaneously processed through, can achieve almost the same accuracy as the existing rule-based ones without them: phase shifting, scaling, noising, and temporal shifting.

References

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