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On the estimation of optoacoustic waves in retinal laser therapy using Gaussian processes

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Abstract: In this paper, we study potentials of machine learning in terms of Gaussian processes (GPs) to learn optoacoustic (OA) waves generated in eye globe during retina laser therapy. This can be utilized to improve temperature measurements for feedback laser control and to understand the tissue properties of the irradiated sites on the retina. The treatment of each site is performed in two phases: The first one is used for GP learning based on measurements from an ultrasonic transducer and its dynamical model, then, the learned GP is employed for estimating the waves during the second phase where the treatment process is activated. The results demonstrate the effectiveness of the approach.

I. Introduction

An optoacoustic (OA) approach has been recently introduced [1] for providing a noninvasive real-time monitoring of retinal tissue temperature during laser treatment, which allows feedback control approaches to regulate the temperature rise [2]. The idea is to repetitively irradiate the retina with laser pulses, which excite the irradiated spot to generate bipolar OA pressure waves propagating through the globe of the eye, which can be detected at the cornea via a transducer. The amplitude of such wave is proportional to the temperature to be obtained of the irradiated spot via a so-called Grüneisen coefficient. However, it is very difficult to detect the amplitude of an OA wave from the noisy signal of the transducer, which includes its dynamics as well as its response to other reflections in the medium. Therefore, heuristic ways are often used in practice, potentially leading to large errors.

In this work, we propose Gaussian processes (GPs) to learn these OA waves given the measurements of the transducer. This approach will have an important impact on reducing errors of temperature measurements, which are used for feedback control. Moreover, such waves can carry valuable information about the optical properties of the irradiated sites and the media propagating through, which can be utilized as diagnostic information, such as level of oxygenation in tissue or its structure information [3].

II. Material and methods

For gathering the data, the experimental setup consists of a treatment laser, a pulsed laser and an annular piezo-transducer. We consider ex vivo experiments on pig eyes. A two-phase treatment is proposed for each irradiated spot: in the first phase, a GP learns the OA waves generated from the associated irradiated site at a nominal temperature. Then, the learned GP can be used to estimate the waves thereafter during the second (treatment) phase under closed loop control. For learning or estimation, the transducer dynamics and its measured signal are provided to the GP. The learning phase can be repeated upon the change of the treated spot. Given the GP estimates, the associated temperatures can be obtained directly using the Grüneisen coefficient without any extra heuristic.

II.I. Modeling

The shape of OA waves is important for assessment and analysis. However, it is difficult to record its shape experimentally. To describe its emission and propagation we use the photoelastic wave equation [4]

$$\nabla^2\Psi - \frac{1}{c^2}\frac{\partial^2\Psi}{\partial t^2} = \frac{\Gamma}{\rho c^2}S(x,y,z,t), \quad p(t) = -\rho\frac{\partial\Psi}{\partial t}, \quad (1)$$

where Ψ is the velocity potential, ∇^2 is the spatial Laplacian operator, c, ρ are the speed of sound and the density in the medium, respectively, Γ is the Grüneisen coefficient and $S(x,y,z,t)$ is a source term indicating heat deposited per time and volume related to tissue and applied laser pulse. The solution of (1) gives the time evolution of an OA wave at an observation point on front of the irradiated site. To obtain the resultant OA waves, which excite the transducer surface, its geometry should be considered. Using the approach of [4], we computed the OA wave shown in Fig. 1 (right) based on the laser pulse shown in Fig. 1 (left).

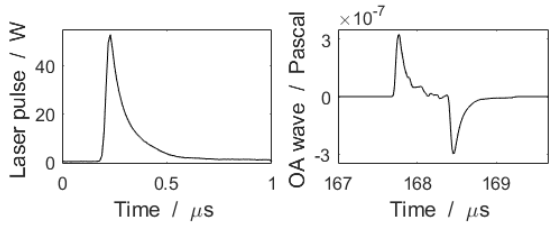

Figure 1: A laser pulse of 6µJ and the corresponding OA wave.

To identify the transducer dynamics, we use system identification based on input-output data. Measured outputs of the transducer are available, but the associated inputs are not. Note that the input consist of the OA wave we want to estimate and other components due to reflections in the medium. To provide an input for system identification, we used the computed OA wave by (1); therefore, a 6^{th}-order liner model for the transducer has been obtained.

II.II Learning and inference

A GP [5] is a generalization of a normal distribution, it can encode a prior knowledge about a function with mean and covariance. Next, we show how GPs can infer OA waves.

Let the transducer model be given in state-space form with an unknown input, i.e., the OA wave to be estimated. A GP model will describe such unknown input. We consider a simple covariance function for the GP prior of the OA wave, the exponential kernel (EK) $\kappa(t,t';\sigma,\ell)=\sigma^2 e^{\frac{t-t'}{\ell}}$,

where σ,ℓ represent its hyperparameters, optimizing them based on measurements is referred to as GP learning. A GP with the EK can be represented as a state-space model driven by white noise [5]. This allows GP inference to be solved efficiently by Kalman filtering. Then, we can combine both sate-space models. Next, the hyperparameters, i.e., σ,ℓ, of the augmented state-space model can be determined by optimizing the marginal likelihood based on the output measurements of the transducer. Once σ,ℓ are calculated, the learning phase is terminated and they are fixed in the second phase. Then, the learned GP can be used like a Kalman filter for estimating the OA waves given the corresponding transducer signal.

III. Results and discussion

To validate the transducer model, Fig. 2 shows its response to an OA signal and the corresponding measurement. The model captures well only the transducer dynamics of the first part of the signal. Note that the measurement includes other exciting sources, e.g. low frequency reflected waves.

Now, we illustrate the performance of the GP. To exclude the effect of the transducer modelling, we have trained the GP on the output of the transducer model corrupted with white noise based on a computed OA wave at $T=20^{o}$C. Then, the learned GP has been utilized to estimate the wave at $T=41.8^{o}$C. Fig. 3, shows that the estimated wave is the same as that one used to excite the transducer model.

To test the GP with real transducer signals of an irradiated site on the retina, the implementation was carried out offline. We used the data of the first phase at $T=20^{o}$C, for learning. Then, the learned GP was employed to estimate the waves of the second phase, while the tissue temperature is elevated, given the associated transducer measurements. As a representative result, Fig. 4 shows the estimation of the OA wave at 41.8^{o}C and the corresponding computed wave. For comparison, we are interested in the first part of the estimated signal; Fig. 4 shows that its amplitude is different from the computed wave. The estimated signal includes also other components, which might have excited the transducer. When we simulated the transducer model with such estimated wave, its response was the same as the measurements used in the estimation as shown in Fig. 5. This demonstrates that the GP performed well based on the available transducer model; however, the difference in the amplitudes in Fig. 4 indicates an insufficiency of the model.

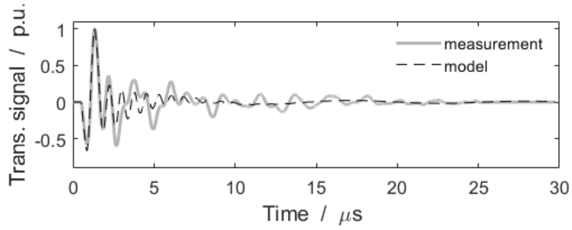

Figure 2: Transducer measurement compared to its simulation.

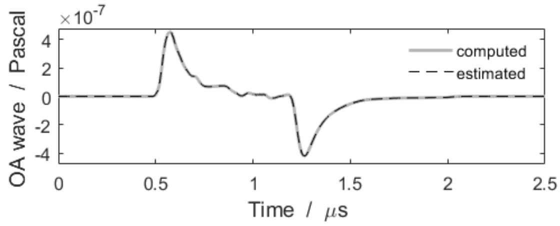

Figure 3: Computed OA wave compared to its estimation.

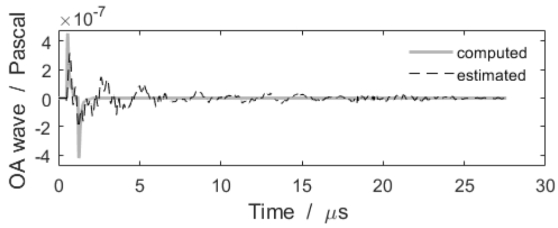

Figure 4: Computed and estimated OA using real measurements.

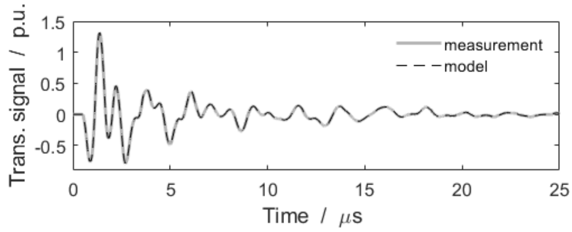

Figure 5: Measurement and simulation using estimated wave.

IV. Conclusion and outlook

We have demonstrated that GPs can be used efficiently to extract OA wave data from the associated transducer measurements, provided good models for its dynamics. This data will be useful for improving related information of tissue in retinal laser treatment. Our next step is to identify transducer models based on dedicated experiments and to enhance the GP models with appropriate kernels.

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