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Supervisory System for Robot Assisted Laser Phonomicrosurgery

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Abstract— **This paper presents the development of a system capable of generating safety alarms when unexpected or unforeseen situations are detected during larynx phonomicrosurgery. Such system establishes relations between the application of laser power and changes in laryngeal tissue characteristics and appearance. As core component, we propose a model able to map inputs generated by the surgeon when controlling the laser to an estimation of tissue temperature. Situations where this supervision is relevant have been identified.**

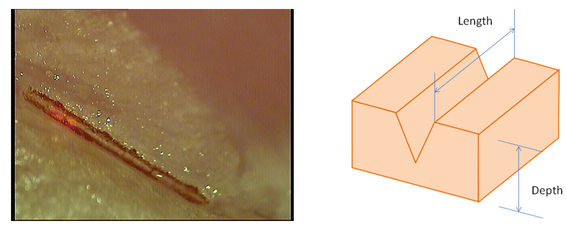
I. INTRODUCTION

Over the last decades the use of lasers as surgical tools has gained wide acceptance in a number of medical specialties. Laser phonomicrosurgery (LP) is one example. It encompasses a set of minimally invasive surgical procedures for the excision of lesions of the vocal folds [1]. Lasers play a significant role in enhancing the quality of phonomicrosurgery as they allow to perform extremely precise and clean incisions, thus minimizing damage to healthy tissue around the lesion that should be preserved in order to save as much organ functionality as possible [2]. The clinical success of this kind of procedures is measured according to the specific type of pathology being treated. Two indicators of the quality of the surgical outcome are *(i)* the recovery time the time needed by the patient to recover after the operation and *(ii)* the degree of restored voice functionality.

With respect to traditional surgery, where precision and quality of incisions depend mainly on the surgeon's delicate sense of touch and on the force feedback he gets from the scalpel, procedures that involve the use of a surgical laser require a different type of dexterity.

Based on these observations, the EU project μRALP [3] proposes to redesign the current LP setup. Through research and development in a range of topics – including human-machine interface, assistive systems, medical imaging, endoscopic tools, micromanipulators – the project aims to advance the state of the art in this kind of procedures, raising its level of accessibility, precision and safety. The ultimate goal is the creation of an advanced surgical robotic platform, allowing surgeons to perform operations that would not be possible using the current technology. Such a platform will enhance the surgeon's perception of the surgical site and support his decision-making process by means of an information-rich interface based on augmented reality.

Within this context, the project entails the creation of a *Cognitive Supervisory System*. The goal is to develop an intelligent system capable of establishing cognitive relationships between the application of laser power and the modifications that the laryngeal tissue undergoes. The purpose of this system is to predict the continuous appearance changes of the surgical site that can be observed during LP, by means of image processing and artificial intelligence techniques. This predictive functionality will be used to automatically supervise the surgical procedure, generating alarms in case unexpected of unforeseen situations are detected. This kind of cognitive supervision will improve the safety of procedures, complementing the surgeon's perception of the state of the LP. Moreover, it will help in detecting faulty hardware conditions, such as variations of laser power or changes in laser focus. This paper describes the technical advances in the development of such a system.



(a) Carbonization (b) Incision Quality

Fig. 1

II. LASER SURGERY SUPERVISION

A top-down approach has been used to define this module. First, those situations where a supervisory system could be of interest were identified and then contrasted against available sensing and processing capabilities. The interaction between the laser and the tissue is the elemental building block at the core of laser-based surgery, which is the process by means of which incisions and dissections are performed. Therefore, the focus of the supervisory system falls on the undesired and potentially dangerous situations that may arise during laser-tissue interaction. In this context, tissue carbonization (Fig. 1a) and incision quality (Fig. 1b) were recognized as potential targets to be automatically supervised.

A. Tissue Carbonization

This is the most relevant type of laser-tissue interaction to be supervised. It is described in the literature as an undesired effect that has to be limited as much as possible [4], [5]. Carbonization during laser incisions indicates that the tissue has suffered thermal damage, i.e. it was burned during the cutting process. This mainly occurs on tissue surrounding the area of incidence, where the temperature becomes very high.

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It is a non-intentional tissue damage where healthy tissue that should have been preserved is being compromised. It causes a longer healing time for the patient, it may leave scars and make any histopathological analysis of removed tissue impossible. These arguments have also been stressed by the surgeons when consulted for those situations that must be prevented during surgery. Moreover, manufacturers of commercial equipment for laser surgery, such as Lumenis Inc. [6], offer open loop minimization of carbonization as an important feature of their most recent products. Unfortunately, actual avoidance of carbonization still relies on the experience and skills of the surgeon which intrinsically establishes how likely carbonization is and thereby decides the laser actions to perform. Certainly, surgeons do not solve the very complex differential equations that govern the dynamics of the phenomena involved during carbonization (e.g., tissue temperature); instead they use a different set of input variables, extracted from visual information, allowing them to interpret the state of the laser-tissue interaction.

B. Incision quality

Another important feature required during laser-based surgery is the performance of high quality incisions. Quality of incision encompasses accuracy for both, depth and length of the cut executed by the surgeon. Such accuracy depends on the capabilities of the laser system to provide the adequate amount of energy and, at the same time, on the ability of the surgeon to control the exposure time of such energy.

C. Autonomous Supervision

It is well known that the phenomena described in the previous sections depend on the variation of temperature of the tissue, as well as its water content, during laser exposure. On the other hand, these variables depend on properties of the surgical laser including beam size, power, pulse duration and exposure time. The laser wavelength and its corresponding absorption and scattering coefficients on the tissue also determine the dynamics of carbonization and the incision quality. The inability to measure tissue temperature during surgery is the first constrain to overcome. Therefore we start developing a model of tissue temperature dynamics during laser interaction. The change in temperature due to heat transfer and transport are modeled as functions of laser exposure time; such model is parameterized with respect to laser power and assumes constant tissue properties. This model was extracted, by means of machine learning techniques, from data generated using Monte Carlo-based simulation of laser propagation inside the tissue plus a finite difference method of heat transportation. Such learned model is essential in order to predict carbonization and to control the incision depth (ablation) during laser surgery.

III. Temperature Dynamics Model

Exact solution of the analytical model of temperature dynamics is complex [4] and it involves several approximations and assumptions. Numerical methods are commonly used to solve the required time dependent equation of temperature.

This section presents a methodology aiming to learn a model of tissue temperature dynamics during laser-tissue interaction, such model uses the same inputs as humans to estimate tissue temperature. This model is not supposed to replace the surgeon's perception but to complement it, performing the same type of cognitive mapping that the human is doing to estimate the state of the tissue given known inputs.

A. Model Definition

Let us define $\mathcal{T}$ as the set of temperature values T^n of the N discrete volume elements that compose the tissue, that is

$$\mathcal{T} = \bigcup_{n \in \{1,\ldots,N\}} T^n, \tag{1}$$

where n denotes a single elemental volume lying at a given radius (r), and depth (z). Temperature dynamics is independent of the angular dimension [4], hence it has been dropped. Let us define $\mathbf{T} \in \mathbb{R}^{I \times J}$ as the temperature matrix that completely describes $\mathcal{T}$. The goal of this approach is to find a discrete model able to describe the evolution of temperature across the tissue volume over time, i.e. the temperature dynamics of tissue, which is expressed as

$$\mathbf{T}_{k+1} = f(\mathbf{T}_k, \mathbf{u}_k), \tag{2}$$

where $\mathbf{T}_k$ is the temperature at time k and $\mathbf{u}$ is a vector representing the independent variables affecting the state of the system. The output of the model is the estimated variable, i.e., the temperature in the next sample time, ($\mathbf{T}_{k+1}$). Input variables for the model must include enough information to predict the output. For this reason, the state of the variable being supervised has been included ($\mathbf{T}_k$). Moreover, we can hypothesize that, given a certain type of tissue and a set of laser properties, such as laser type and beam size and profile, changes in temperature are only driven by the laser power (P) and length of the pulse duration (τ), i.e.

$$\mathbf{u}_k = [P \quad \tau]^T. \tag{3}$$

Eq. (2) assumes a known and constant sample time (t_s)

We hypothesize that a single function can be used to map the inputs to the prediction of the temperature in any point (r, z) of the tissue volume. There exists a unique function, h, such that,

$$T^{i,j}_{k+1} = h(\mathbf{T}_k, \mathbf{u}_k, i, j)\Box \tag{4}$$

The function proposed in Eq. (4) is clearly nonlinear, as the influence of $\mathbf{u}$ is not proportional with respect to the location of volume elements. The assumptions presented in the previous section, together with the required approximation for the initial temperature $\mathbf{T}_0$, restrict the use of the model only to similar types of laser and tissues as well as similar environmental conditions. Moreover, this model does not take into account laser motion, as it assumes the point of application of the laser on tissue to stay fixed during the exposure. Despite more complex models may be envisioned, this model will allow to validate the proposed methodology and will constitute the basis to achieve more ambitious objectives.

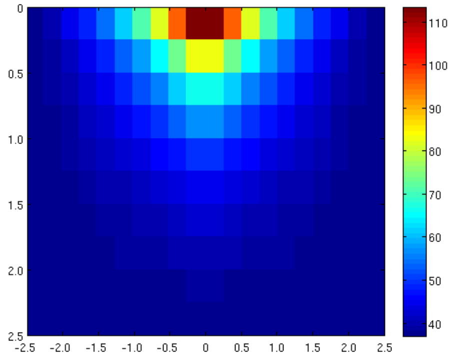

Fig. 2: Section view of temperature distribution across the tissue geometry after simulated laser-tissue interaction. Tissue has been exposed for 4 seconds to a CO_2 laser beam, 0.025mm large. A power of 1W and with a pulse time of 0.2s have been used.

B. Learning temperature nonlinear dynamics

A supervised learning algorithm, known as Locally Weighted Projection Regression (LWPR) [7], [8], is used to approximate the function hypothesized in Eq. (4). The method requires the availability of a set of training examples, i.e. a set of samples of the input and output variables $\left\{\mathbf{T}^l_{k+1}, [\mathbf{T}, \mathbf{u}]^l_k\right\}^m_{l=1}$. LWPR was selected as learning method as it is considered the state of the art in statistical nonlinear regression. It permits to learn nonlinear functions from large a amount of training examples, characterized by a high dimensionality of the input space. Moreover, being an incremental method, it can be fed with new training data at any time, allowing to craft models able to adapt to changing circumstances [7].

C. Simulated laser-tissue interaction

A computational simulation of temperature dynamics during laser-tissue interaction was developed, as proposed in [9], [10], to the aim of collecting the training examples needed. The optimal approach to acquire such training examples would be to capture data from actual laser-tissue interaction experiments. Experiments of this kind have already been proposed in other works, such as [11], for different research objectives. As a validation mechanism of our concepts, this paper presents a temperature model learned using simulated data. However, validation with respect to data collected in a real laser-tissue interaction is also presented.

The simulation combines a Monte Carlo method, to model energy absorption, with a finite difference method which models heat diffusion within the tissue medium. Fig. 2 reports an example of temperature distribution obtained through the implemented simulation. Temperature increases the most at the center of the tissue surface, where the laser beam has been applied. Heat exchange phenomena dominated the temperature dynamics in the rest of the tissue, leading to smaller increments.

IV. Cognitive System for Surgery Supervision

Based on the model proposed in Eq.(4), an autonomous system to avoid tissue carbonization and to supervise the quality of the incision can be implemented . The endoscopy surgical setup proposed in the µRALP project [3] includes the use of high-resolution cameras that will provide visual perception to the surgeons. Image processing techniques has been already implemented [12] in order to trace the location of the (usually read) beam of the laser. Giving such location, the proposed model can be distributed over the area of interest, activating the input when the surgeon triggers the laser, generating and tracking the estimate tissue temperature. Beyond estimating the temperature, the energy transferred to the tissue after reaching vaporization point ($\approx$ 100°C) can also be estimated and tracked, allowing the control of the incision quality (depth and length).

V. Analyzing Model Response

A total of 200 laser interactions were simulated for the generation of the training data set. Each simulation has a randomly selected duration of laser exposure and equal amount of time for temperature evolution without the presence of the laser (P=0W), i.e. the process of cooling down was also simulated. The training data was generated using diverse pulse rate given a fixed power (P=2W), i.e. diverse effective values of fluence rate. Four types of pulse rates were considered (Continuous Wave, $\tau = 0.1s, 0.2s, 0.5s$), 50 experiments were simulated for each pulse rate. The learning process uses a total of 627120 samples and the obtained model presents a normalized mean square error (nMSE) of 3.7% against the learning data set. The validation data set, with 176880 samples, presents a nMSE of 4.3%. These results demonstrate that given a temperature of a volume element together with the temperature of its surroundings and the fluence rate being transferred from the laser, the learned model is able to estimate the temperature for such volume in the next time step.

Besides verifying standard learning and validation errors, further tests and analysis are necessary in order to verify the quality of the model. The consistence of the model as a dynamical system must be tested, recursively using its prediction as input for the next estimation. Convergence of the predicted temperature with respect to laser-tissue simulations is expected. Fig. 4 presents a comparison of the temporal response of the learned system with respect to the reference dynamics. For the case of continuous laser mode, the learned model accumulates a nMSE = 4.2%, while for the case of pulsed laser mode the nMSE = 3.74%.

VI. Experimental Results

The presented results are part of the development of a system intended to operate during real laser ablation, to support and complement the perception of the surgeon. As a step in this direction, data from real laser-tissue interaction must be collected, allowing an assessment of the strengths and of the weaknesses of the model. So far, it has been demonstrated that the learned model acts similarly to the

Fig. 3: Experimental setup

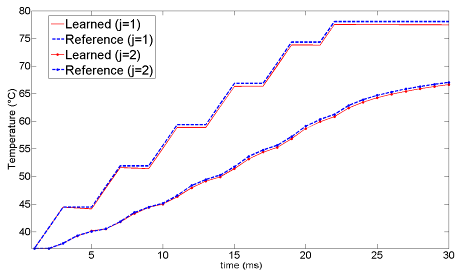

Fig. 4: Temperature dynamics at the center of the tissue at the surface ($T_{1,1}$), and at $z = 0.025$mm, ($T_{1,2}$) for pulsed laser mode. Time response of the reference (blue) and learned (red) models are shown.

Monte Carlo simulation. However, the quality of such simulation has not been discussed yet. This sections presents the initial results towards the validation of the applicability of the model and the required improvements. An experiment has been performed, applying a 10.6μm laser beam generated by a CO_2 surgical device onto samples of chicken tissue. The time required to ablate the tissue (Tissue Ablation Time) has been measured. This time corresponds to the time required to raise the temperature of the point of application of the laser to $100°$, plus the time required to vaporize it (Ablation by vaporization). Fig. 3 shows the experimental setup.

Results presented in Table I were obtained executing 5 experiments for each pulse mode. The reported TAT corresponds to the mean of the measured event. It can be seen that, as presented in the results section, the dynamics of the temperature for the continuous pulse mode (CW) is much more faster than the one obtained with the $\tau = 0.1s$ mode.

VII. CONCLUSION AND FUTURE WORK

This paper proposed a cognitive model for carbonization prediction during laser-tissue interaction. The model is based on the measurable variables within a surgery setup: high level information extracted from video processing as well as the history of laser actions. The proposed model is based on inputs similar to those used by the surgeon during the operation and not on the exact measurement of tissue temperature and laser dynamics. This model may help during surgery to complement the perception of the practitioners on the state of the interaction, enhancing the human decision making process aiming to avoid carbonization. Moreover, it

TABLE I: Tissue Ablation Time

Pulse Mode	TAT
CW	343ms
0.1	433ms

may be used to automatically adjust the laser properties to obtain better results in specific stages of the surgery.

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