Optical Tomography-based Soft Sensor Skin

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Abstract— **Sensing and locating pressure stemming from the physical interaction between a soft robot and its environment is crucial for deploying such robots in real-life scenarios. Sensors capable of high sampling rates are necessary to adapt the robot's real-time behaviour. This extended abstract summarises a soft sensor skin and sensing strategy for optical tomography-based systems. The optical skin consists of a transparent sensing layer with twenty-four optical fibres transmitting light into the transparent layer and twenty-four optical fibres transmitting light from the sensing layer to a camera. Unlike traditional tomography systems that transmit light through the soft sensor sequentially, we proposed a strategy that concurrently illuminates the sensor with multiple light sources and reads out the sensor response. We conducted experiments to demonstrate that our approach enables robust pressure estimation and contact point localisation with up to 91.1% accuracy (compared to 70.3% at a lower sampling rate).**

I. Introduction

Soft robotics has become increasingly popular in recent years, mainly because of the compliance that enables them to work safely in human-robot interactions. This compliance, on the other hand, also creates challenges in modelling the kinematics and controlling the soft robots [1]. Soft sensors have been proposed to sense external and internal stimuli without compromising the advantageous degrees of freedom offered by the soft bodies of these robots. Various sensing technologies have been used in developing these compliant sensors, such as resistive [2], capacitive [3], [4], magnetic [5], and optical [6], [7].

This article discusses a novel tactile sensing strategy for optical tomography-based skin sensors. This sensing strategy allows for faster and more accurate pressure estimation and localisation as compared to the traditional or sequential switching strategy as presented by [8].

II. Materials and Methods

In optical tomography, the analysis of the light transmitted and scattered through an object can help us to estimate the geometry and structure of that object. When probing soft transparent materials, optical tomography can be applied to estimate the pressure that caused the deformation of the sensing material.

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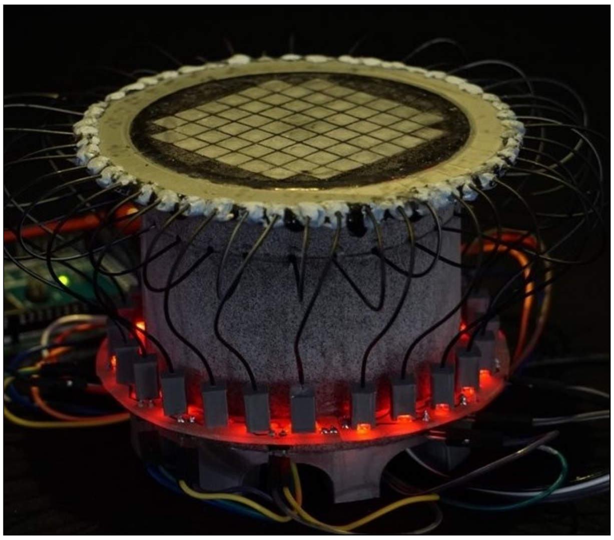

Fig. 1: This figure shows the experimental setup consisting of an optical skin laid on a 3D-printed tray that holds the optical fibres. The tray is fixed on a 3D-printed hollow cylinder that acts as camera housing and PCB holder for the LEDs.

The skin sensor design employed in this study is quite similar to the one introduced in a previous work [8]. It consists of a soft, transparent layer made of a 1.2mm-thick Solaris Smooth-On layer. This transparent sensing layer has 24 emitters and 24 receivers optical fibres embedded into it. To transmit and receive red light with a wavelength of 633nm, we used 1mm-diameter optical fibres (Mitsubishi ESKA FF-SH 2001-J). To isolate the transparent SOLARIS layer from ambient light, we added a soft 0.2mm-thick black EcoFlex 00-30 layer on top of it. Our skin's total diameter measures 80mm, with optical fibres embedded 7.5mm into the transparent layer, resulting in an effective sensing area with a diameter of 65mm. To assess our skin's spatial resolution, we divided this area into 60 sectors by brushing aluminium powder onto the top of the protective black EcoFlex layer with a spatial resolution of 7.5mm.

To individually control each LED, we connected them to a Raspberry Pi 3B+. This setup enables us to carry out sequential and concurrent LED switching and compare the two tomography methods using the same connections. Instead of using individual photo-sensors, we opted for a commercially available webcam to estimate the light intensity of each optical fibre as it is both cost-effective and compact. Receiver optical fibres carrying the light out of the sensing medium are held in front of the camera, giving us feed at a resolution of 1280x720 pixels at a rate of 30 frames per second.

To exert pressure, a flat-ended indenter with a diameter of

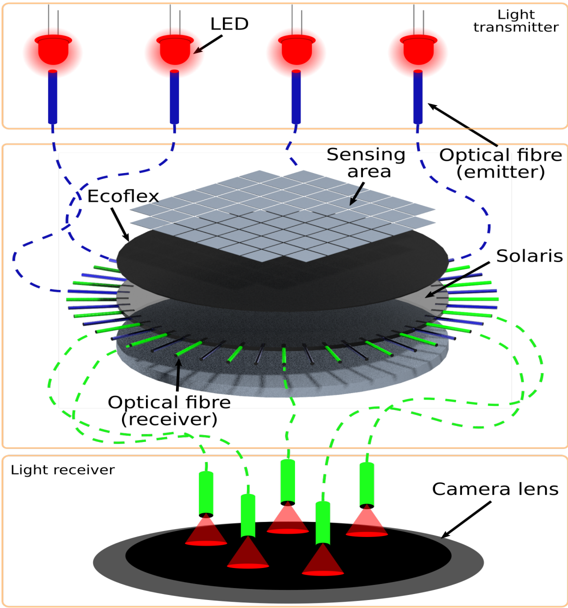

Fig. 2: Soft sensor skin based on optical tomography using optical fibres as a means to emit and receive light. The skin can easily be applied on any surface and only contains soft and deformable components, without any embedded electronics.

5mm is fixed to an Instron 5967 Universal Testing Machine to apply, step by step, a sequence of 18 forces per node. The range of force the machine applies increases from 0.2N to 3N in increments of 0.2N, with additional forces of 0.5N, 1.5N, and 2.5N included. 30 samples were collected for each force and each node resulting in 1800 samples for both sequential and concurrent switching. We also collected 1800 samples with no indention to keep the data balanced. For estimating the force and the location, we employed Machine Learning models available in `scikit-learn` library [9].

III. Results and Discussion

The accuracy and F1-score for each of the three classifiers used to predict pressure localisation for both data collection strategies are shown in the table I.

TABLE I: Accuracy and F1-score comparison for node localisation between sequential and concurrent switching of LEDs for 3 classifiers

	AdaBoost		Random Forest		SVM	
	Acc.	F1	Acc.	F1	Acc.	F1
Sequential	0.542	0.555	**0.703**	0.697	0.699	**0.706**
Concurrent	0.656	0.669	0.903	0.898	**0.911**	**0.907**

It is noteworthy that the accuracy and F1-score reported in Table I are consistently higher for concurrent LED switching, regardless of the classifier. For concurrent switching, the SVM classifier performed the best with an accuracy of 91.1% and an F1-score of 90.7%.

For each data collection approach and for each regressor, the final RMSE obtained on the validation and test sets is reported in Table II.

TABLE II: Validation and test RMSE comparison for pressure estimation between sequential and concurrent switching of LEDs for 3 regressors

	AdaBoost		Random Forest		SVM	
	Valid	Test	Valid	Test	Valid	Test
Sequential	35.2	35.7	**24.1**	**30.9**	37	36.4
Concurrent	32.4	32.6	**14.5**	**17.2**	26.6	27.7

It is quite evident from the II that the pressure estimation results are consistently better for concurrent switching. Random Forest performs the best for forces from 50.93 kPa and 152.79 kPa, even for unseen data. At pressures below 50.93 kPa the regressors report higher RMSE.

IV. Conclusions

The paper proposes a new approach for optical tomography, where all light sources are switched on concurrently instead of sequentially. This results in a significant increase in the sampling rate and improved pressure localisation and estimation performance. The localisation accuracy is reported to be 91.1% for concurrent, with a maximum error of 7.5mm, and is 20% better than sequential switching. The sensor can also accurately estimate pressures of 50.93 kPa or above. The future work includes the performance improvements of the sensor skin by using deep learning. Moreover, we also intend to run experiments for multiple contact detection.

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