Sensitivity of Acoustic sensing to pressure in soft robotic fingers

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***Abstract*— We analyze the influence of pressure on the prediction ability of acoustic sensing technique in soft robotic fingers. The method uses a single air chamber soft fingers with an embedded speaker and microphone. Two hypothesis corresponding to contact force and speaker volume were proposed. Fingers being inflated to different pressure levels, static contacts are made with different objects. This produces a unique sound signal for different events enabling the prediction of contact states. We experimentally demonstrate that the hypothesis holds to an extent. Also, we could not observe an established relationship between pressure and prediction ability of acoustic sensing.**

I. INTRODUCTION

We use sound to identify the static contact location between the soft robotic fingers and the object. Sound sensing technology provides information about the contact states while being low cost and does not negatively affect the compliance of soft fingers during manipulation tasks. Traditional electronics sensors and hardware provide hindrance by restricting the manipulation surface and being costly. We test the sensitivity of sound technique in presence of pressure in soft fingers. This sensitivity analysis demonstrates the reliability on acoustic sensing technique.

Acoustic sensing have been proven as an novel sensing technique. The embedded speaker and microphone in air chamber of a soft fingers enables the detection of contact states. The design can be viewed in [1]. The experiments were based on the principles of acoustics [2]. This technique relies on unique sound signals generated from contact events between soft fingers and contact objects. With an ability to sense contact locations, contact force and type of contact materials [1].

We monitor two parameters, viz, contact force and speaker volume in order to examine the reliability of acoustic sensing in presence of pressure. For higher value of these parameters we expect better performance. Data sets collected over different fingers produce results in support of the expectation while certain data points produce surprising results. The exact relationship between inflation pressure in soft fingers and state estimation ability of acoustic sensing technique was not established. While, the results provided guidelines for understanding the involved relationship.

[1]

[1]Author undertook this project with Robotics and Biology Laboratory (RBO) at Technische Universtität Berlin, Germany. We thank Vincent Wall for supervising the project and Veranika Paulava for construction of the soft robotic fingers. Also, the members from RBO laboratory for discussions and involvement in the project. `https://gitlab.tubit.tu-berlin.de/khush123/RBO-Lab-Acoustic_sensing_ws19.git`

II. RELATED WORK

A. Acoustic sensing for soft robotic fingers

Sensor technologies involving inflexible electronics hardware [3] restricts the ability of soft fingers for grasping tasks. An cost effective sensor layouts can be generated for desired applications [4] Sound has been used with microphones to recognize objects upon an contact [5], for detection of materials [6]. These techniques measure the world properties. While, [1] takes advantage of sound modulation occurring in sound structure-borne sound in sound-carrying structure to reconstruct the contact locations, contact forces and type of materials in contact.

III. TECHNICAL SECTION

A. Classifying soft robotic fingers

The experiments were performed on four different soft robotic fingers. Fig.1 presents 'leaky' fingers- leakage of air mass from the finger during experiments and manually brought back to initial value. Also, 'Non leaky' fingers that were able to hold air pressure throughout experiments.

B. Embedded acoustic sensors

The embedded speaker and microphone in soft fingers are demonstrated in [1]. The sound generated by speaker placed near the tip of the finger is received by microphone placed at the bottom. The speaker emits a frequency sweep that travels through the finger and retrieved by the microphone.

C. Experimental setups

- Initially experiments were performed with finger 1 without measuring the contact force and pressure levels. Based on visual sight, the pressure levels and forces were classified as low, medium and high.
- Further, setup 2 involved F/T sensor Mini40 [7] for force measurements and compressor for pressure measurement. F/T sensor was fixed and contact was made by a human holding the finger as visible in Fig.2(b). This setup was used for recording datasets 2 and 3 with fingers 2 and 3 respectively. Similarly, setup 3 was used for recording dataset 4 with finger 4.

D. Classifying the contact states

Six contact locations are considered around the finger to make contact with the object. These are based on an idea of entire finger becoming an sensor as stated in [1]. The contact states were tip, middle, base, left, top and right as visible in Fig.3 .

(a) Finger 1

(b) Finger 2

(c) Finger 3

(d) Finger 4

Fig. 1: Different fingers for recording datasets

E. Classifying the force ranges

The force measurement using F/T sensor in x,y,z direction were F_x, F_y, F_z respectively. Resultant force obtained is given by the equation:

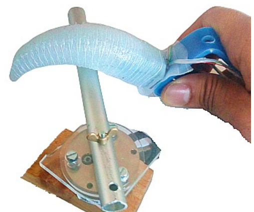
$$F = \sqrt{(F_x)^2 + (F_y)^2 + (F_z)^2} \tag{1}$$

This resultant force F was restricted to lie in different ranges. The different force ranges considered for net force F were range1: 0 N to 1 N, range2: 1 N to 2.8 N and range3: 2.8 N to 5.2 N. Accordingly, the three observable deformation is seen in Fig.4.

F. Classifying the inflation levels

- For finger 2, the pressure levels were varied from 30 kPa to 80 kPa with an increment of 10 kPa in consecutive levels. This caused changes in the finger curvature as shown in Fig.5. The maximum pressure level was limited to 80 kPa for the scope of experiments so as to safely have contact states with the object avoiding contacts at multiple locations.
- For finger 3 - an 'leaky' finger pressure levels were initially set to 30, 50, 70 and recording would be done till pressure fell back to 10,30,50 respectively. Likewise, dataset 4 recorded with finger 4, consist of pressure levels 30, 50 and 70 kPa.

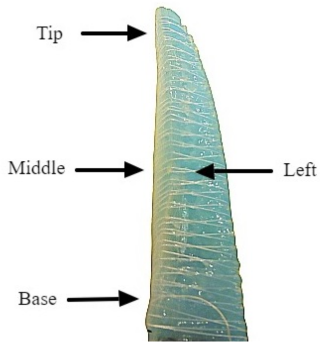
(a) Setup 1 with finger 1



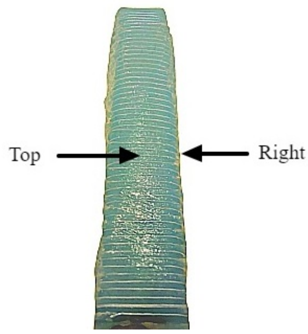
(b) Setup 2 with fingers 2 and 3

(c) Setup 3 with finger 4

Fig. 2: Experimental setups



(a) Setup 1



(b) Setup 2

Fig. 3: Six contact location around the finger

G. Predicting contact states with Machine Learning

The classifier is based on scikit-learn library [8]. Each experiment consists recording of 150 samples. This involved 25 samples for each of six contact states. These samples are classified into 5 sets each consisting of 30 samples. Training is performed over 3 sets while testing on remaining 2 sets of data. This is repeated using 10-fold cross-validation and an average prediction accuracy is reported. The prediction is done using KNN technique with k=5 over all datasets for all fingers.

H. Speaker volume hypothesis

We propose that speaker volume is directly proportional to the energy of the sound wave that is imparted into the finger. Higher the speaker volume, higher is the energy of the imparted sound wave. As the internal pressure in the finger provides an hindrance for propagation of wave, some energy is lost. An hypothesis that a higher energy wave

(a) Force range 0 N - 1 N

(b) Force range 1 N - 2.8 N

(c) Force range 2.8 N - 5.2 N

Fig. 4: Contact force range between finger and object

(a) 30 kPa

(b) 40 kPa

(c) 50 kPa

(d) 60 kPa

(e) 70 kPa

(f) 80 kPa

Fig. 5: Pressure levels for finger 2

would be received better by microphone with information about contact states. This would help in attaining better sweep prediction accuracy.

I. Contact force hypothesis

As the finger makes a static contact with the object, its surface gets deformed. The extent of deformation is dependent on the contact force as shown in Fig.4. It is known that more deformation on the finger surface would lead to modulation of the sound wave. Thus, contact state information would be stored in the sound wave as it got modulated. A hypothesis that higher contact force results in deformation, eventually leading to information stored in sound wave. This would enhance the prediction accuracy when received by the microphone.

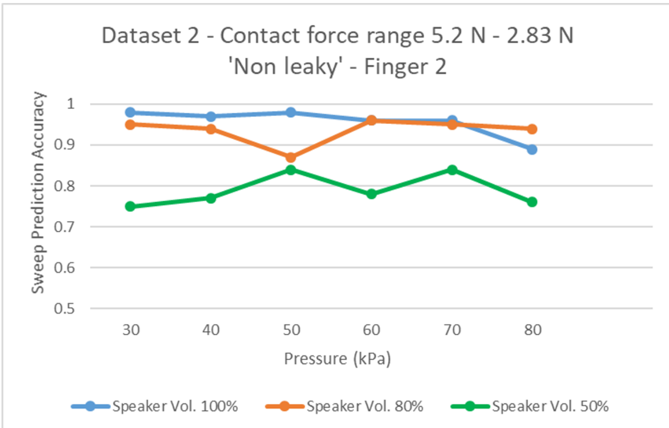


Fig. 6: Dataset2 with various speaker volume levels

IV. Experimental Results

A. Analysis of speaker volume hypothesis

To examine the hypothesis, dataset2 and dataset4 were recorded for force range: 5.2 N to 2.83 N. Two key observations from Fig.6 and Fig.7 were noted.

- The comparison between data-lines from speaker vol.100% along with speaker vol.80% with speaker vol.50% agree with the proposed hypothesis. While comparing speaker vol. 100% with speaker vol.80% do not completely get along.

- We could not observe a regular pattern in any of the specific data lines.

B. Analysis of contact force hypothesis

To examine the effects of various force ranges, we had the speaker volume constant for recording datasets with different fingers. Accordingly data recorded with fingers 1, 2 and 3 yield results. Key observations from Fig.8, Fig.9 and Fig.10 are:

- The Fig.8 provided the base for contact force hypothesis. The evidence is visible through the data set. The drastic decrease in prediction accuracy in low force range when pressure increases from low to medium is not fully explored. A general pattern

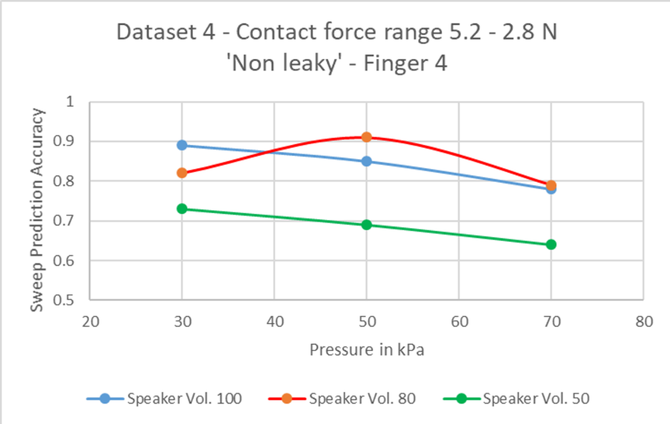


Fig. 7: Dataset4 with various speaker volume levels

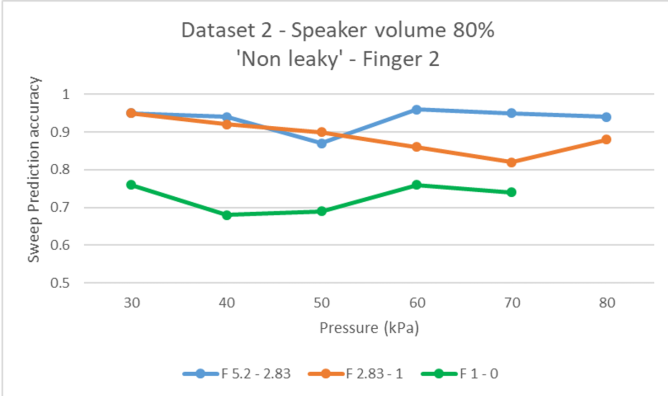


Fig. 9: Dataset2 for different contact force ranges

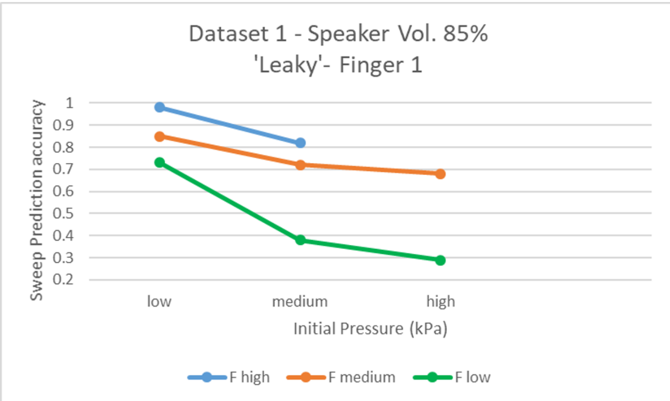


Fig. 8: Dataset1 for different contact force ranges

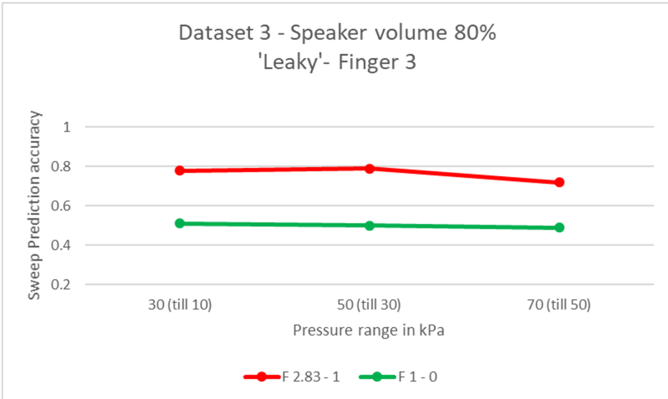


Fig. 10: Dataset3 for different contact force ranges

seems to exist- increase in pressure decreases prediction accuracy, but due to limited data points and experiments being prone to error (due to leakage in the finger1) we proceed with dataset2.

- Fig.9 illustrates that hypothesis holds when we compare data-line from force range: 0 to 1 N with other two data-lines. While, at pressure 50 kPa the accuracy for force range: 2.83 to 1 N is surprisingly higher than force range: 5.2 to 2.8 N.

- Fig.10 holds the hypothesis but with limited data points we cannot make a concrete decision.

- We could not observe a regular pattern for data-lines corresponding to Fig.9 and Fig.10.

C. ML trained model for different force pressure levels

We trained an machine learning model with training data from all data points (17 in total) from Fig.9 Thus, the training data consisted different force and pressure levels with an aim to predict a certain pressure level with KNN technique (k=5). So, for example to predict pressure level 30 kPa, the test data set consist of test-set (3 in total) from three force levels.

The model yields good results for predicting different pressure levels. The obtained prediction accuracy is higher compared to any individual force data-lines. The key observation is that data from different force levels (at an specific pressure) helps to better predict the pressure levels.

V. Conclusion

- The key idea for the project was to reconstruct contact states using sound modulation. A research is conducted to understand how the contact states can be reconstructed in presence of pressure. Two hypothesis corresponding to contact force and speaker volume were proposed. Both hypothesis holds for majority of data sets, while some data points do not align and produce surprising results.

- The four data sets provide discrete data lines for sweep prediction accuracy constructed over various pressure levels. A regular pattern could not be observed with these data lines. Dataset 1 seems to follow a trend,but it has been prone to error due to finger leakage and limitation of data points. So, this trend is less likely to exist.

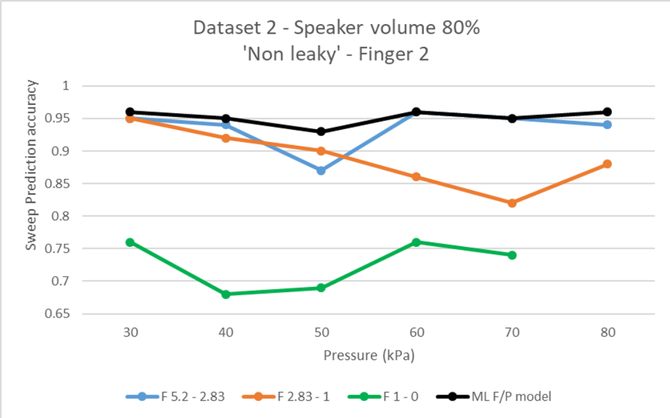


Fig. 11: ML model predicting the specific pressure level

- For the reason mentioned above, we could not establish an concrete relationship between pressure and prediction accuracy. A more detailed analysis involving more data points and parameters can be performed to better understand the relationship. Monitoring the two parameters was the contribution to the ongoing research in acoustic sensing technology.

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