Non-Invasive Glucose Monitoring utilizing Electromagnetic Waves

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ABSTRACT
We discuss some of our recent experiments using Google's Soli alpha kit on monitoring different glucose levels among various sample sets in-vitro. These experiments are part of our ongoing campaign to investigate the suitability of using mm-waves for non-invasive glucose monitoring among patients with diabetes.

Author Keywords
Google Soli, mm-Waves, Glucose monitoring, non-invasive, electromagnetic scattering.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous; See http://acm.org/about/class/1998 for the full list of ACM classifiers. This section is required.

INTRODUCTION
Diabetes is a disease directly caused by failure of the pancreas in producing a steady supply of hormone insulin, because insulin enables the body's cells to accept glucose in the bloodstream as caloric energy. Unmanaged diabetes among patients could lead to many serious complications such as heart disease, stroke, coma, kidney failure, blindness, amputation, and premature death [1].

Diabetes is classified into two categories: type 1 and type 2. The Canadian Diabetes Association recommends monitoring of blood glucose at least as often as insulin intake (four times daily) for type 1 patients, and two times daily for type 2 patients to meet glycemic targets [2]. To check for blood glucose, blood from the tip of the finger is drawn, and then analyzed on a glucometer. Finger-pricking has been the only medically accepted daily glucose monitoring technique for diabetic patients in north America until as recent as 2012, when the US Food and Drug Administration has approved its first continuous glucose monitoring (CGM) system [3], which uses the so called artificial pancreas as an automated closed-loop glucose detection and insulin administration device that lessens the frequency of daily finger-pricking. However, artificial pancreas also performs glucose analysis invasively through the skin, which is non-ideal or non-feasible in many health situations.

From the perspective of device operation, the methods of glucose monitoring can be essentially categorized as invasive, minimally invasive, and non-invasive. Invasive devices detect glucose from subcutaneous or intravenous bodily fluids: besides analyzing glucose level via blood drawn from the finger, there are wireless implants with radio frequency capabilities to communicate glucose data to an external controller for analysis. Minimally invasive devices detect glucose externally via extracted interstitial fluid from skin tissues. They differ from invasive devices in that the techniques to extract interstitial fluid do not cause significant damage to the tissue. There is discomfort and risks of infection from both invasive and minimally-invasive techniques, and researchers in both academia and industry are working on non-invasive techniques for detecting glucose from external body-fluids such as sweat and tear.

There have been thorough investigations on alternative non-invasive methods of blood glucose monitoring over the last decade. Absorbance spectroscopy techniques, such as near-infrared and mid-infrared spectroscopy [4], have been commonly researched where the scattering of light on biological tissue is used to detect the optical signatures of glucose in blood. However, in addition to being costly to implement, these methods are also highly sensitive to changes to physiological parameters, such as body temperature and blood pressure, as well as environmental variations in temperature and humidity. Several research studies have been done on utilizing bodily fluids to correlate blood glucose concentrations in breath [5], saliva [6] , sweat [7], and tear fluid [8]. Despite being quite innovative, these proposed methods either show a low correlation between the measured parameters and blood glucose levels or the proposed designs are still in their infancy to judge their applicability [9].

On the other hand, radio frequencies have also been investigated for applications in continuous blood glucose monitoring. The presented concept designs generally involve measuring the reflection and transmission coefficients through the skin (and hence the dielectric constant and permittivity of the blood) with transmitters and receivers placed near areas such as the finger tips or ear lobes [10,11,12]. Almost all published works use a single channel deterministic VNA system (1 Tx to 1 Rx), with significant mounting and alignment issues that hinder the possibilities of realizing a user friendly system. Alignment and repeatability are known problems in bio-identification, and our recent work with Soli's [16] multi-channel AI/ML engines have demonstrated a working prototype [13]. We have also had very decent success with gas detection [14]. While other teams successfully demoed object identification [15]. Encouraged by the recent successes, we have been investigating the potentials of using Soli [16] in glucose monitoring.

SANITY CONCEPT CHECKS

We started our measurements campaign with a simple question: Can we use a multi-channel radar to differentiate among a coke, diet coke, and zero coke? Fundamentally, each drink has a different amount of sugar dissolved. We ran our tests using a 4-port Keysight N5227A PNA-67GHz Microwave Network Analyzer. Each port was fitted with V-band adapters connected to WR-15 horn antennas beneath glass cups holding the drinks. It was very clear that even just one channel reflection data were enough to easily differentiate among all drinks as depicted in Fig. 1 (showing the magnitude of the reflection coefficient in all three cases) and Fig. 2 (showing the unwrapped phase of the reflection coefficient in all three cases). Clear differences are also noted in other inter-port coefficients (not plotted here for brevity).

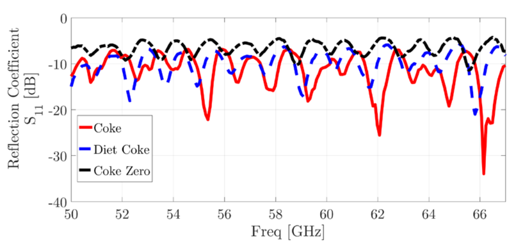

Fig. 1. Scattering parameter data using a 4-port VNA.

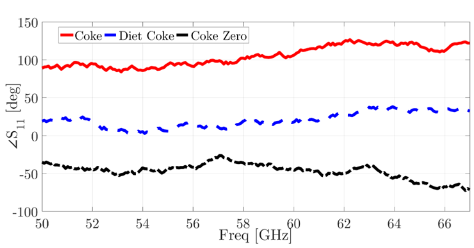

Fig. 2. Unwrapped phase of the input reflection coefficient for one port of the 4-port VNA.

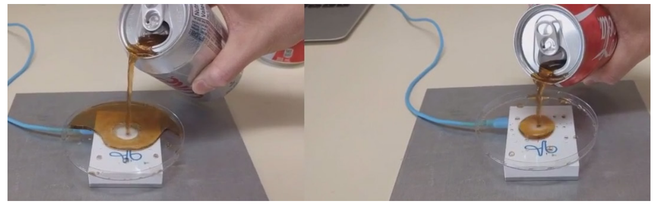

Fig. 3. Experimental setup using Soli.

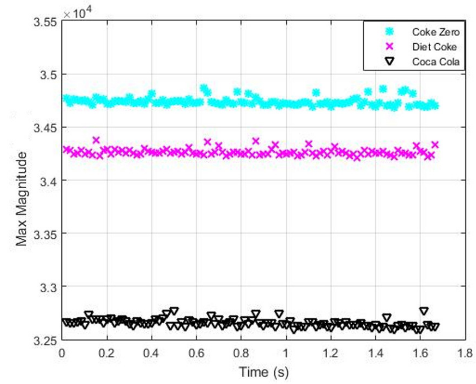

Fig. 4. Max magnitude of one of the Soli channels for the different coke drinks.

We repeated the same experiment but using Soli rather than the 4-port analyzer. Soli has a 2 Tx and 4 Rx radar system, thus effectively capable of detecting minute differences in the reflected waves as a rich multi-channel system [16]. We used machine learning to "educate" the Soli to detect different drinks regardless of the container and exact position with respect to Soli. Fig. 3 demonstrates one of the experimental setups. The measurements taken with the radar sensor as the training data were utilized to create a classification model generated through a random forest classifier. The random forest classifier is a supervised machine learning algorithm that is composed of a series of decision trees. A decision tree maps any observation of the data to a conclusion about the object's value. In the context of this work, the four processed data metrics along with the magnitude of the backscattered signals (such as that shown in Fig. 4) form the observations of the object, while the predicted glucose-water concentration is the object's value. At the end of decision tree process, the most prevalent conclusion reached by all the decision trees is outputted as the object's predicted value. The accuracy of the classification models can be expressed via the percent likelihood of the model returning the correct prediction. To summarize the performance of the classification models, confusion matrices were used to show the percent likelihoods of different combinations of true and predicted values. The resulting confusion matrix likelihoods for the different cokes measurement was consistently in the high 90% demonstrating a remarkable detection accuracy.

FURTHER EXPERIMENTS

To model human blood, samples of glucose-water at healthy and diabetic blood sugar level concentrations were used and a series of measurements were done to find the lower limit and resolution of the radar sensitivity. For a 2 hour post-prandial diagnosis, a person is considered to be diabetic if their blood glucose levels exceeds 2.0 mg/mL, while a healthy person's blood sugar levels generally falls below 1.4 mg/mL [17]. During fasting, the blood glucose levels of a healthy person is expected to fall below 1.08 mg/mL while diabetics exceed 1.26 mg/mL [17]. With these concentrations in mind, the ability of the radar to discriminate between five samples of glucose-water with concentrations ranging from 1.0 mg/mL to 2.0 mg/mL at 0.25 mg/mL increments was tested.

We summarize here three distinct set of measurements: Glucose-water samples in Petri dish, 3D printed ear-model with Glucose-water solution, and meat slices soaked in the glucose-water samples.

Case 1: Petri-dish

Fig. 5 displays the data from one of the Soli channels when using the Petri dish for different concentrations. Similar to a very expensive VNA system, it is clear that SOLI can be used to reliably distinguish between different concentrations.

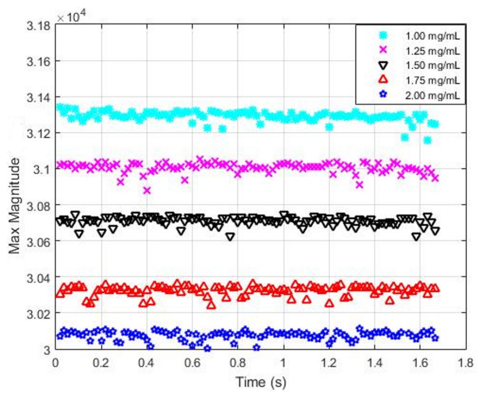

Fig. 5. Max magnitude of one of the Soli channels for the different concentrations.

Case 2: Using the 3D printed ear model

Since the human skin is not perfectly planar, a 3D model replicating the curvatures of the human ear was used to demonstrate the performance of the concept system (Fig. 6). The ear was selected since the thickness of the skin around the earlobe region is minimal and ideal for blood glucose measurements. The ear model had an ear lobe thickness of 1.1 mm and was made from a silicone rubber-carbon black composite. Small amounts of glucose-water were injected into the earlobe section to simulate blood flowing in the earlobe. Fig. 7 displays select Soli raw output when using the 3D printed ear model. Again, it is clear that SOLI can be used to reliably distinguish between different concentrations.

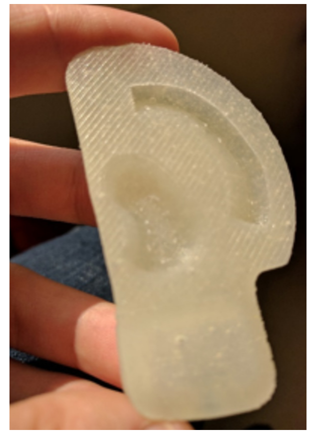

Fig. 6. 3D printed Silicone Ear model

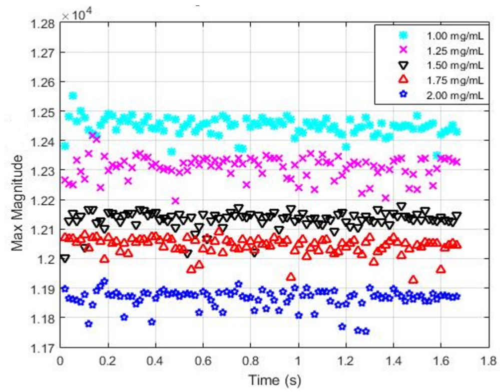

Fig. 7. Max magnitude of one of the Soli channels for the different concentrations using the silicone ear model.

Case 3: Using cow meat

The next set of measurements used slices of cow meat with 1 mm thickness to asses if the mm-Wave signals emitted by the radar can adequately penetrate biological tissue of this thickness. All pieces had nearly an identical cut, dipped in a glucose-water solution of a given concentration, and each piece of meat utilized was measured first using a VNA. Unlike previous cases, the scattering parameters were nearly identical in all cases (See for example Fig. 8). However, the phase data was unique among each case (such as depicted in Fig. 9). Such fundamental differences in the scattered waves helped Soli resolve such subtle differences in concentrations as shown in Fig. 10.

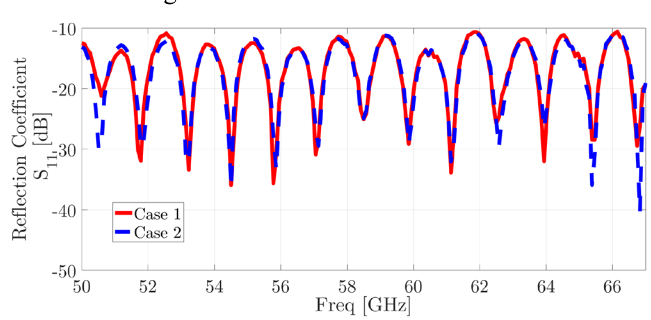

Fig. 8. Scattering parameter data for the meat in 2 different glucose-water concentrations using a 4-port VNA.

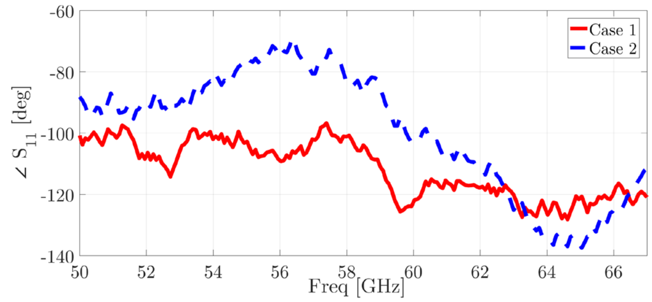

Fig. 9. Unwrapped phase of the input reflection coefficient for one port of the 4-port VNA when observing the behavior meat in 2 different glucose-water concentrations.

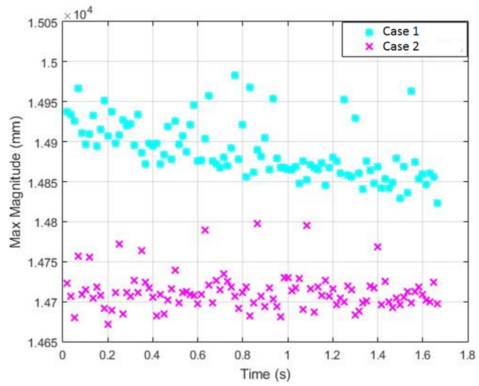

Fig. 10. Max magnitude of one of the Soli channels for the different meat/glucose-water concentrations.

CONCLUSIONS AND DISCUSSIONS

Using pop drinks and various concentrations of sugar water near blood glucose ranges for diagnosing diabetes, we showed the sensitivity of Google Soli system in being able to discriminate between various glucose-water concentrations at a high accuracy. We utilized silicone rubber structures and animal meat as human tissue-equivalent phantoms for further validations.

We are currently running a large campaign with various actual blood samples to further investigate the suitability of using a system like Soli in non-invasive glucose sensing.

However, it should be stressed that despite having promising preliminary results, this area is still in its infancy, and we believe that there is tremendous research due before non-invasive electromagnetic-based monitoring of diabetes through skin can become a reality. Among the many challenges to address is the fact that scattered electromagnetic energy through skin/blood stream is known to vary with naturally varying physiological parameters such as moisture levels, sweat, temperature, and tissue scarring. Such variations can significantly affect the detection system. Attempts to minimize their impact are part of our ongoing research campaign.

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