

RSAC[®]Conference2015

San Francisco | April 20-24 | Moscone Center

SESSION ID: MBS-F01

Side-Channels in the 21st Century: Information Leakage From Smartphones

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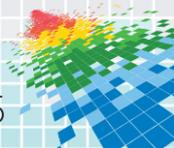
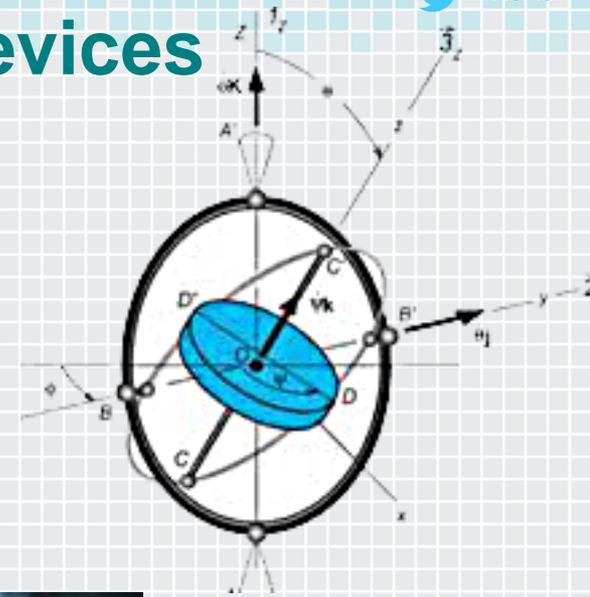
Stanford University
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CHANGE

Challenge today's security thinking



Side-Channel Attacks on Mobile Devices



Session's Main Points

- ◆ Mobile devices are susceptible to information leakage in weird and unexpected ways.
- ◆ Rogue applications might do harm even if they have few permissions.
- ◆ The bottom line: treat every app you install as having 'root' on the phone.
 - ◆ After this presentation you will think twice before installing a “harmless” game from an unofficial market having “zero” permissions.

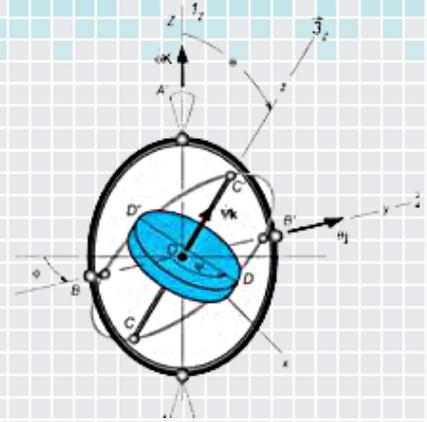


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Sensor ID: Mobile Device Identification via Sensor Fingerprinting

H. Bojinov, Y. Michalevsky, G. Nakibly and D. Boneh



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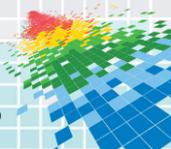
Mobile device identification

- ◆ The research question: Can an app (or a website) identify the device on which it runs?
- ◆ Answer: Yes!
 - ◆ Android: Device ID, Serial number, MAC Address, ANDROID ID.
 - ◆ iOS :UDID, identifierForVendor, advertisingIdentifier, MAC Address.



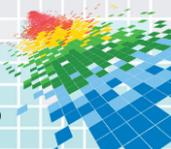
Mobile device identification (cont.)

- ◆ However, all of these standard identifiers either
 - ◆ require the user's permission
 - ◆ can be changed by the user
 - ◆ does not survive factory reset
 - ◆ not good for all mobile device types
 - ◆ can not be used by a web application



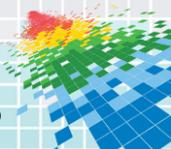
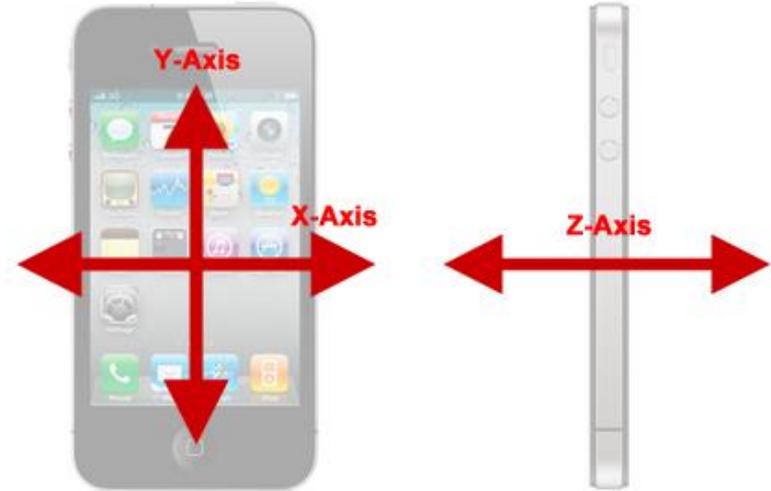
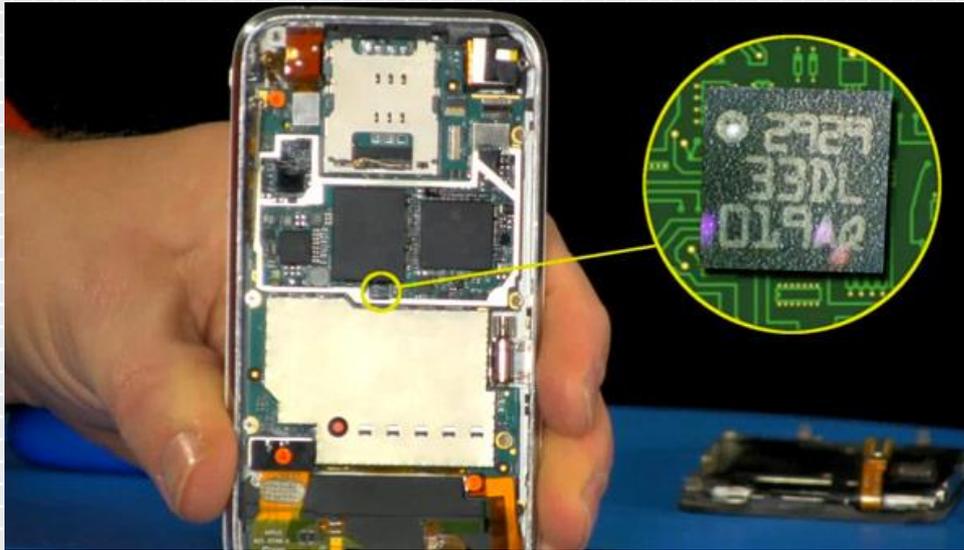
The Basic Idea

- ◆ Each sensor has a tiny inaccuracy that is very specific to it.
- ◆ Such inaccuracies can be used to fingerprint the device.



Accelerometer

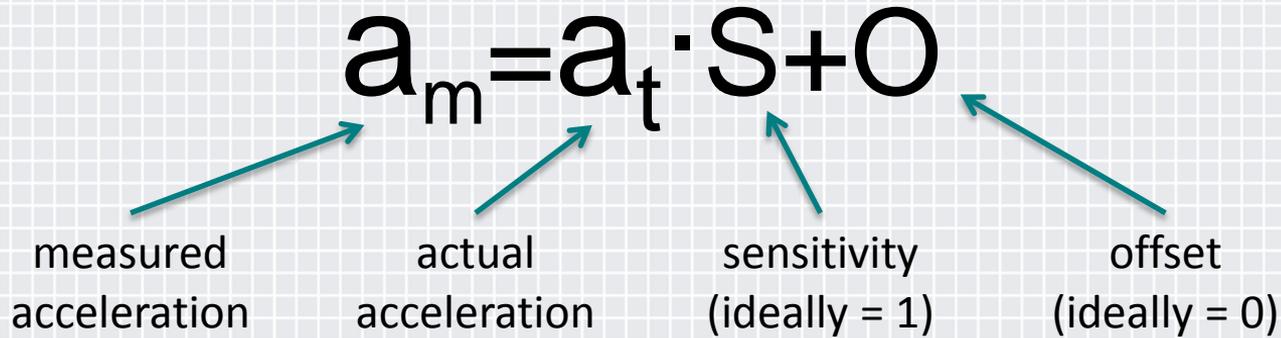
- ◆ Measures the acceleration of the phone in all three directions.



Accelerometer Skew

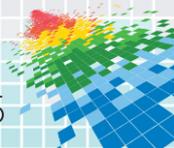
$$a_m = a_t \cdot S + O$$

measured acceleration actual acceleration sensitivity (ideally = 1) offset (ideally = 0)



But how can we measure S and O?

- ◆ We need some reference acceleration...

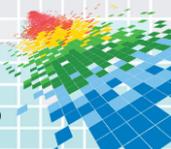
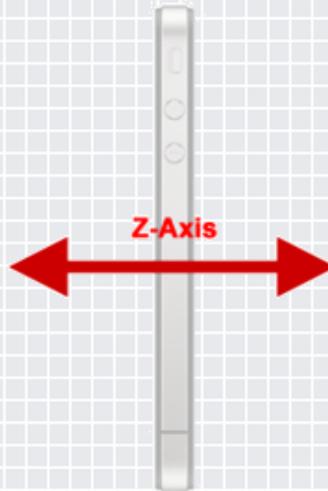


GRAVITY



Measuring S and O

- ◆ As a first step we tried to identify S and O for the Z axis



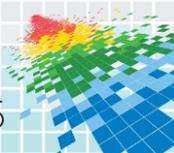
Measuring S and O

- ◆ Measure the acceleration face up and then face down and then do some calculations

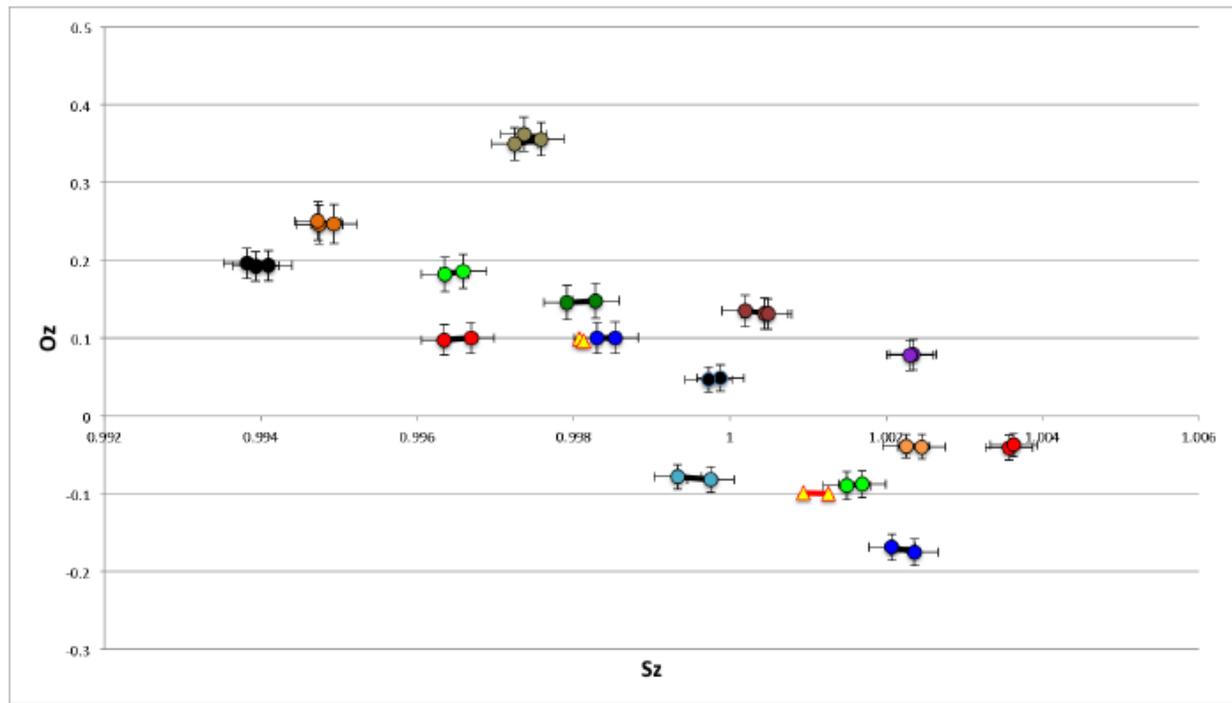


$$S_z = (z_{m^+} - z_{m^-}) / 2g$$

$$O_z = (z_{m^+} + z_{m^-}) / 2$$



Initial Experiment for 17 iPhones

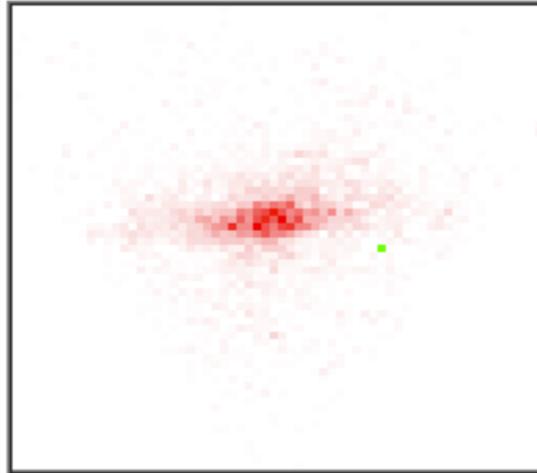


Results for 10,000(!) phones

- ◆ An estimated **7.5 bits** of identification.
- ◆ If we can measure S and O for all three axes we can get $3 \times 7.5 = \mathbf{22.5 \text{ bits}}$ of identification.

Sensor ID Result Chart

your device ID is **(0.341178,1.007)** and it is unique among **17749** records

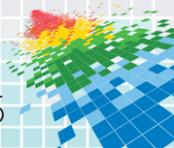


the green square marks your device's ID
more IDs in a cell make that cell more red



Measuring S and O for all axes

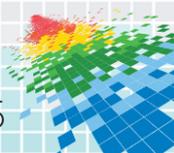
- ◆ A phone does not usually stand up...
- ◆ Alternatively, we can measure the phone in 6 resting positions.



Measuring S and O for all axes

- ◆ And then do some math....

$$\left(\frac{x_m - O_x}{S_x}\right)^2 + \left(\frac{y_m - O_y}{S_y}\right)^2 + \left(\frac{z_m - O_z}{S_z}\right)^2 = g^2$$



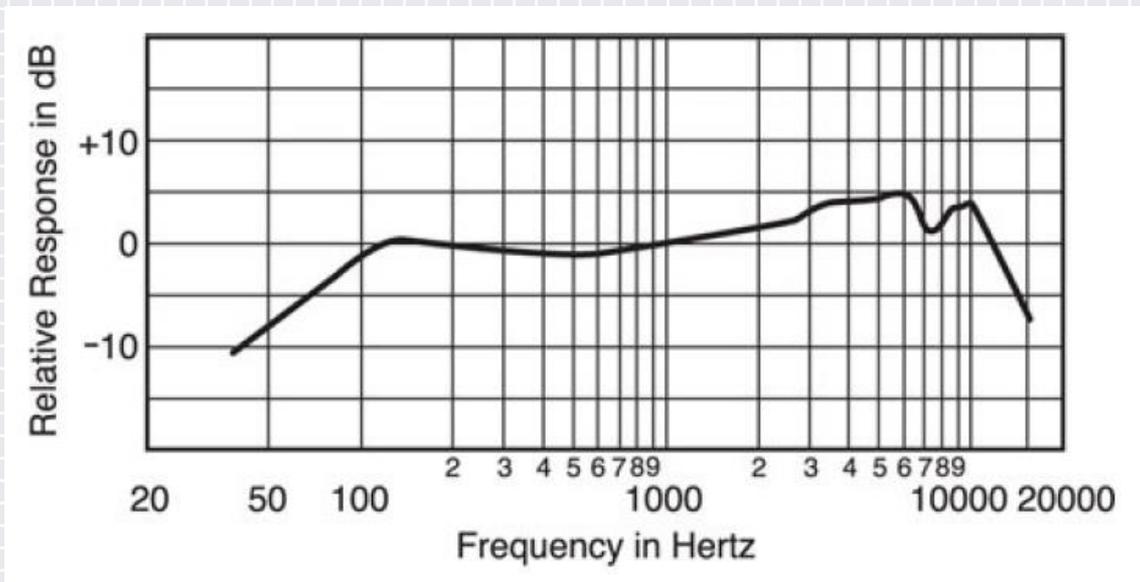
Accelerometer is not alone...

- ◆ Other sensors can also be fingerprinted
- ◆ For example, the microphone



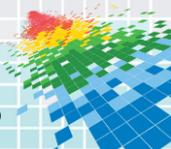
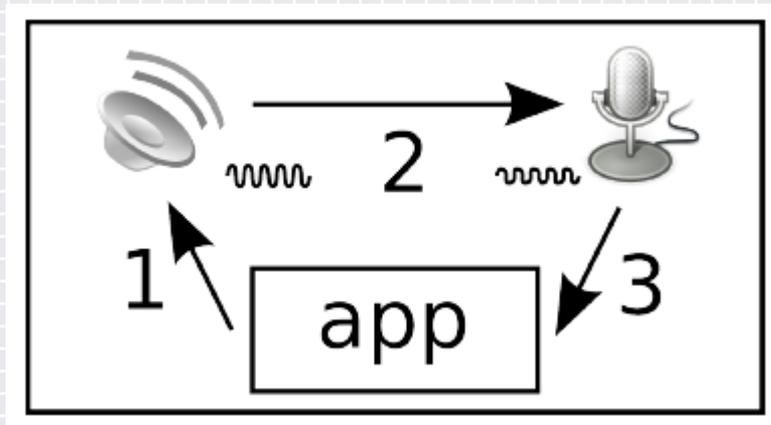
Microphone

- ◆ Each microphone has a characteristic frequency response curve

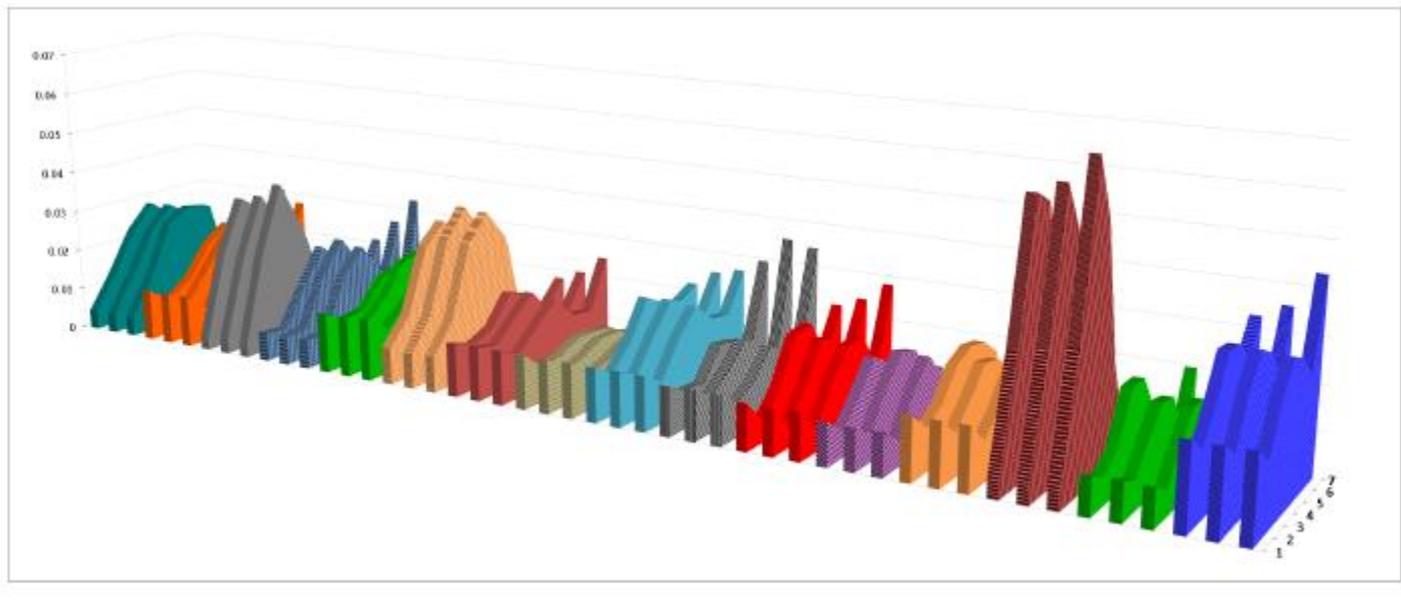


How can we fingerprint a microphone?

- ◆ We need some audio reference....
- ◆ We can usethe phone's speaker



Experiment for 16 Motorola Droids



SendorID – Conclusions

- ◆ We have found ways to construct a device ID by sensor fingerprinting.
- ◆ All the sensors' fingerprints may sum up to enough bits to identify all devices.
- ◆ It is hardware dependent.
- ◆ It can be used by web application.

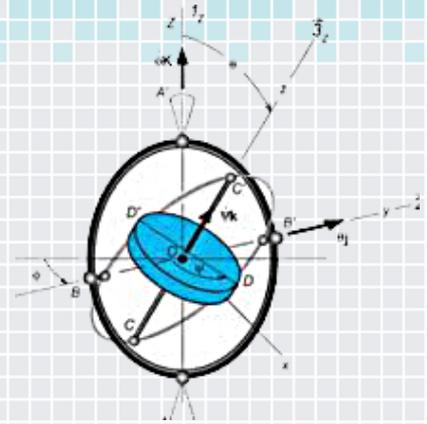


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Gyrophone: Recognizing Speech from Gyroscope Signals

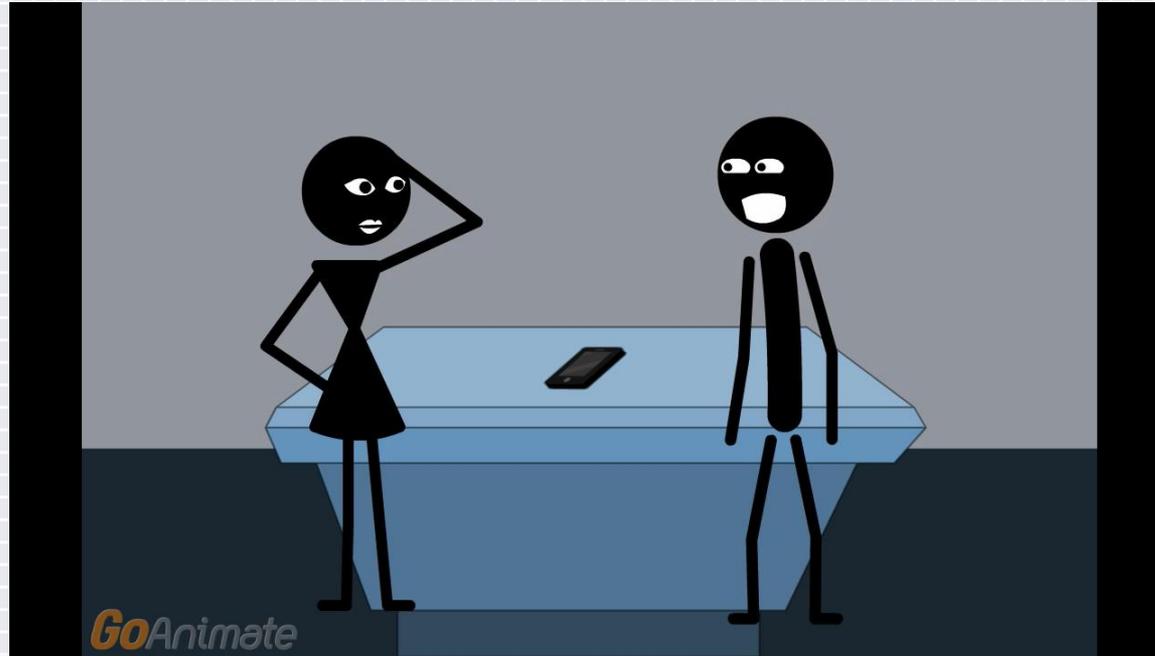
Y. Michalevsky, G. Nakibly and D. Boneh



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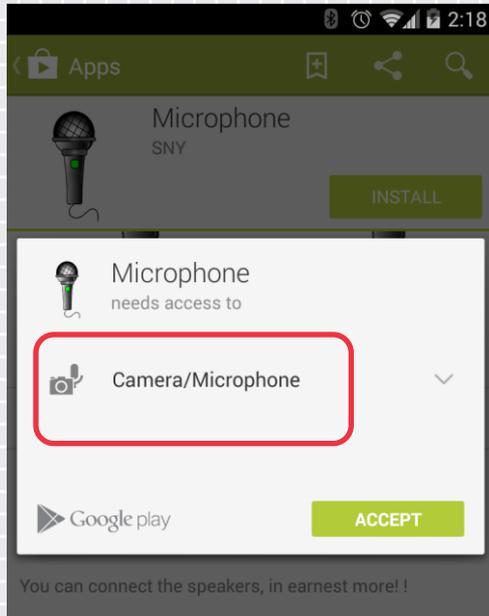
Scenario

People are talking in the vicinity of a mobile device

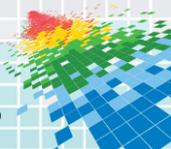
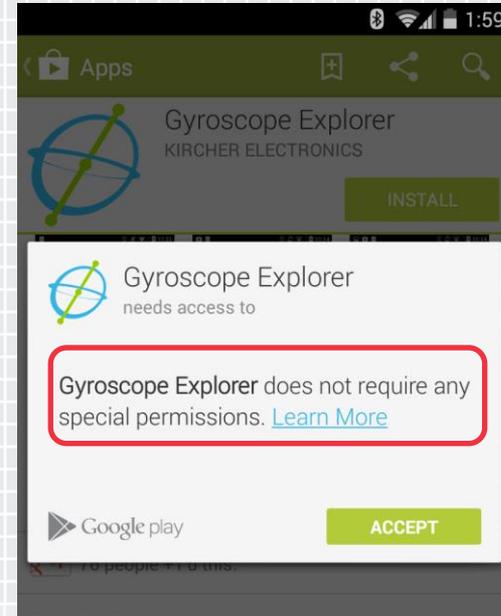


Microphone vs. Gyroscope Access

Requires permission

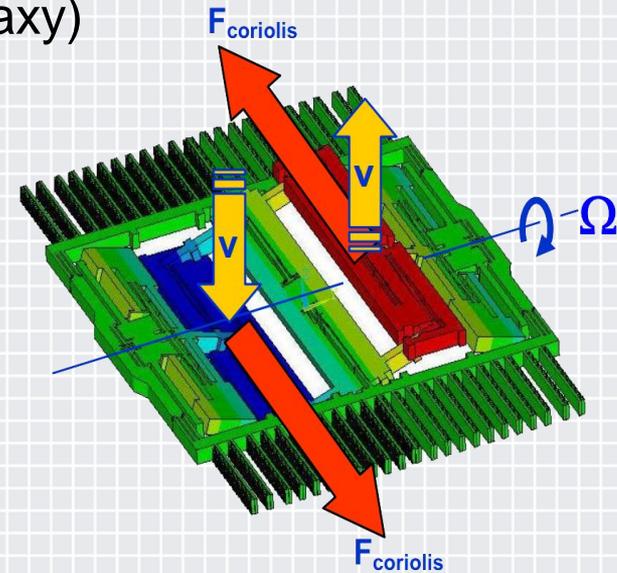


Does **NOT** require permission



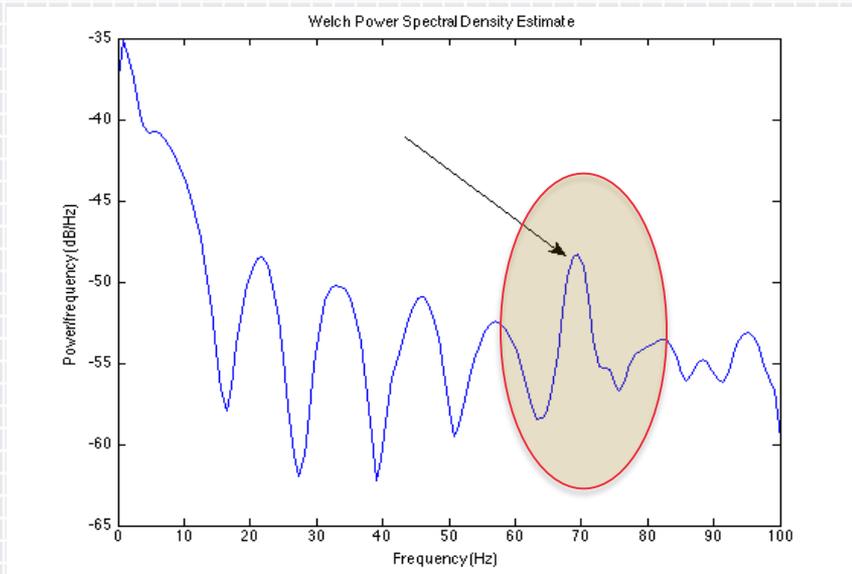
MEMS Gyroscopes

- ◆ Major Vendors:
 - ◆ STMicroelectronics (Samsung Galaxy)
 - ◆ InvenSense (Google Nexus)

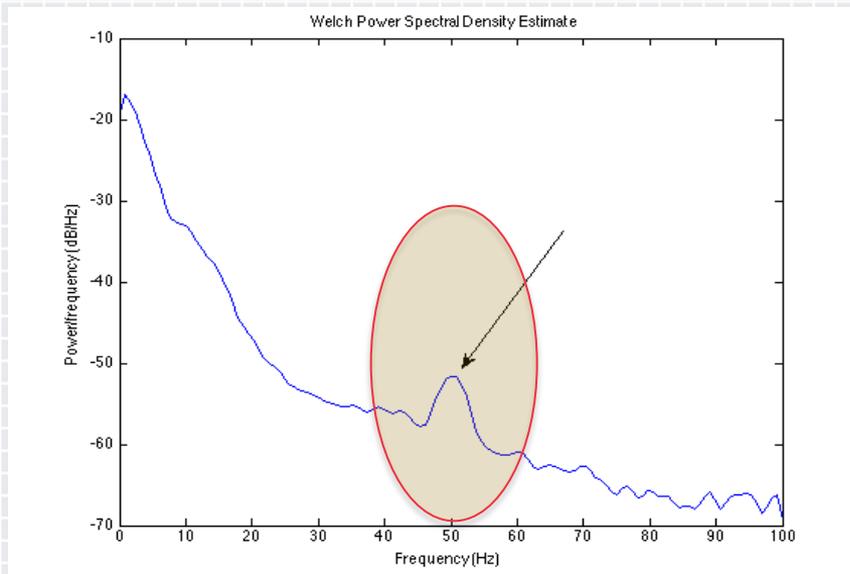


Gyroscopes are susceptible to sound

70 Hz tone PSD

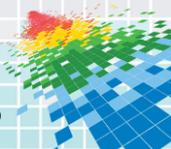


50 Hz tone PSD



Gyroscopes are (lousy, but still) microphones

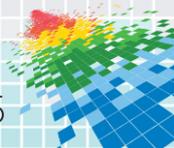
- ◆ Hardware sampling frequency:
 - ◆ InvenSense: up to 8000 Hz
 - ◆ STM Microelectronics: 800 Hz
- ◆ Software sampling frequency:
 - ◆ Android: 200 Hz
 - ◆ iOS: 100 Hz
- ◆ Very low Signal-to-Noise ratio (SNR)
- ◆ Acoustic sensitivity threshold: ~70 dB
Comparable to a loud conversation
- ◆ Sensitive to sound angle of arrival
- ◆ Directional microphone (due to 3 axes)



Browsers allow gyroscope access too

WebApp based browsers

		Sampling Freq. [Hz]
Android 4.4	application	200
	Chrome	25
	Firefox	200
	Opera	20
iOS 7	application	100
	Safari	20
	Chrome	20



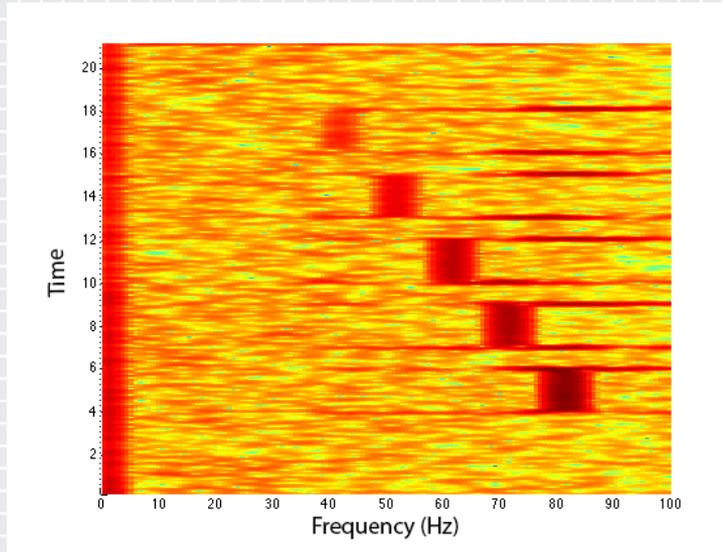
Problem: How do we look into higher frequencies?

Speech Range

Adult Male	85 – 180 Hz
Adult Female	165 – 255 HZ



We can sense higher frequencies signals Due to aliasing



Recording tones between 120 to 160 Hz on a Nexus 7 device



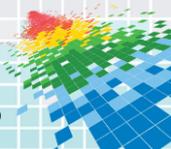
Experimental setup

- ◆ Room. Simple Speakers. Smartphone.
- ◆ Subset of TIDIGITS corpus
- ◆ 10 speakers \times 11 samples \times 2 pronunciations = 220 total samples



Speech analysis using a single Gyroscope

- ◆ Gender identification
- ◆ Speaker identification
- ◆ Isolated word recognition
 - ◆ Speaker independent
 - ◆ Speaker dependent

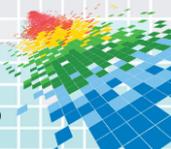


We can successfully identify gender



Nexus 4	84%
Galaxy S3	82%

Random guess probability is 50%

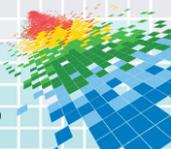


A good chance to identify the speaker



Nexus 4	Mixed Female/Male	50%
	Female speakers	45%
	Male speakers	65%

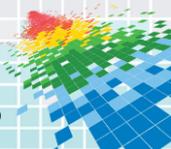
Random guess probability is 20% for one gender, and 10% for a mixed set



Isolated word recognition (speaker independent)

Nexus 4	Mixed Female/Male	17%
	Female speakers	26%
	Male speakers	23%

Random guess probability is 9%



Isolated word recognition (speaker dependent)

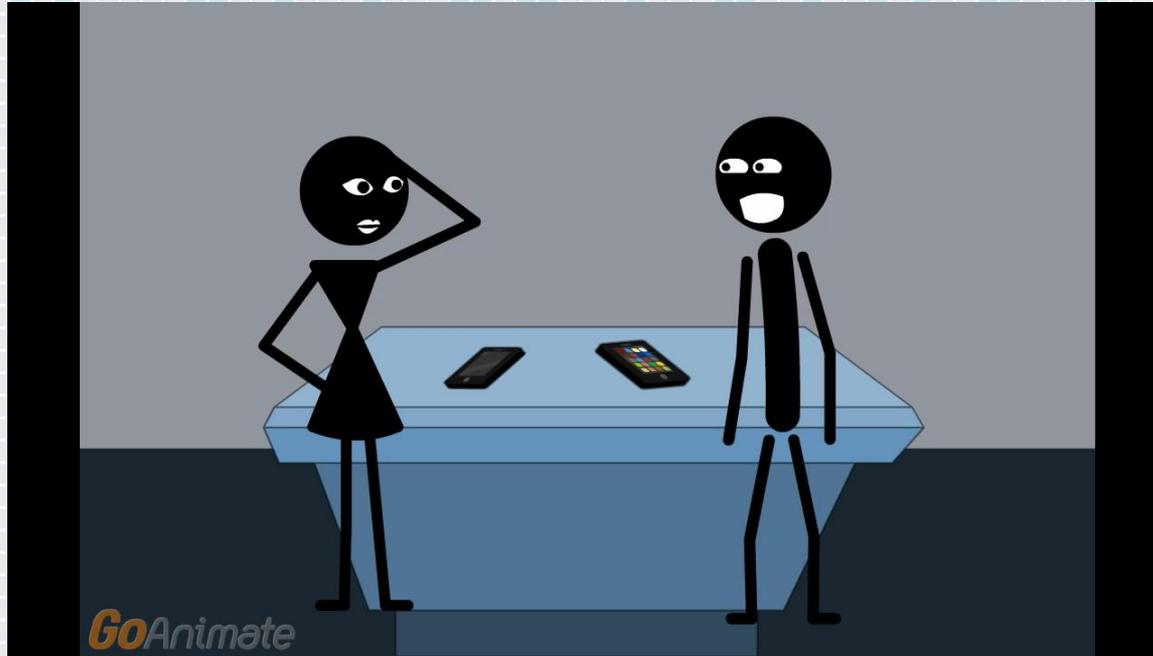
Nexus 4

Male speaker

65%

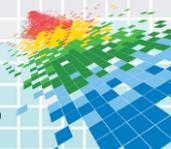
Random guess probability is 9%





Can we use multiple devices to improve the method?

Answer: Yes. Raising speaker dependent recognition rate to 77%.



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Defenses



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Software Defenses

- ◆ Low-pass filter the raw samples
- ◆ 0-20 Hz range might be enough for browser based applications (learning from Web-Kit's example)
- ◆ Access to high sampling rate should require a special permission
- ◆ Can possibly be applied by software providers / open-source community



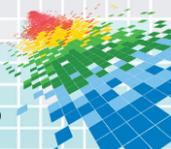
Hardware Defenses

- ◆ Hardware filtering of sensor signals (not subject to configuration)
- ◆ Acoustic masking
- ◆ Can possibly be applied by vendors



More details can be found here

crypto.stanford.edu/gyrophone



To conclude

- ◆ We believe this is only the beginning
- ◆ Many more unexpected information leakages will be found in coming years.
- ◆ Treat every app you install as having ‘root’ on the phone!
- ◆ Now we know you will think twice before installing that “harmless” game



Questions?

- ◆ Yan Michalevsky – yanm2@cs.stanford.edu
- ◆ Gabi Nakibly – gabin@rafael.co.il

