

The Motion Sensor Western

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About Me



Computer Scientist & Former Google Employee

Ph.D. Student @ Ben-Gurion University of the Negev, Israel

Researcher at CBG (Cyber @ BGU)

Research Focus:

Side-channel attacks

Sound recovery via non-acoustic data

Security of autonomous vehicles (drones, advanced driver-assistance systems)

Read more about my research at www.nassiben.com.





Agenda

The Good: Advantages of Motion Sensors

The Bad: Security Risks

The Ugly: Privacy Risks

User study

Takeaways

Q&A



The Good



MEMS Motion Sensors

MEMS (Micro-Electro-Mechanical Systems) motion sensors are electrical devices that utilize a sensor to detect nearby motion.

In this talk we focus on two specific motion sensors

MEMS Gyroscope

A device which is used to measure the angular velocity

MEMS Accelerometer

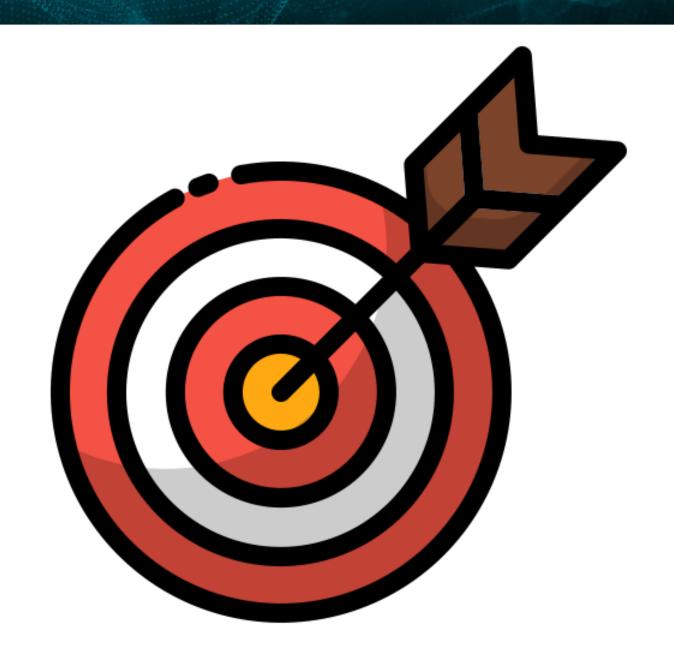
A device which is used to measure the rate of change of a velocity.

Cheap



Cheap

Provide sufficient accuracy



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Low power consumption



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Small



Motion sensors have become more and more ubiquitous.



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Smartphones & Tablets





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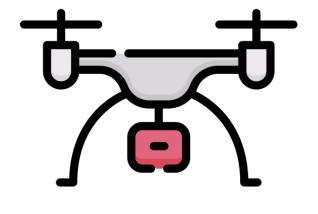
Smartphones & Tablets



Smartwatches & Fitness Trackers



Drones



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Smartphones & Tablets

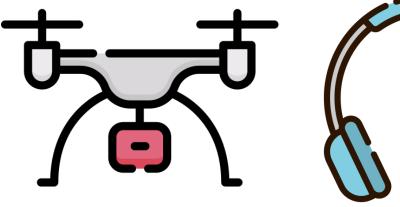


Smartwatches & Fitness Trackers



Drones

Headphones





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Real-time automatic stabilization (drones, GoPro cameras)

Improved gaming experience (turning a smartphone into a joystick)

Real-time user activity recognition (detecting walking)

User health monitoring (counting steps)

Navigation (IMU)

Motion sensors have become more and more ubiquitous. They are integrated in many IoT devices.

Most everyone in the audience is being sampled by motion sensors in at least one device for most of the day.



In 2007, resonant acoustic injection frequency attack was identified as a problem that causes performance degradation of MEMS motion sensors [1] [2].

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Most MEMS gyroscopes [3] and accelerometers [4] have a unique resonant frequency that is related to the physical characteristics of their structure.

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Resonant frequency ranges

for MEMS gyroscopes: 7.9-28.6 KHz

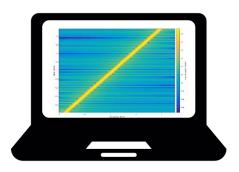
for MEMS accelerometers: 2.2-13 KHz



How attackers can find/identify the resonant frequency of a motion sensor?

Given a motion sensor, the range around the resonance frequency can be detected as follows:

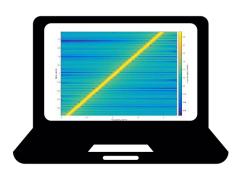
Produce a signal of a frequency scan (chirp).

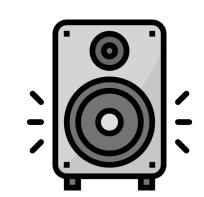


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Play the signal via speakers in proximity to the motion sensor.





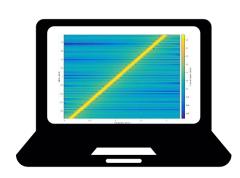


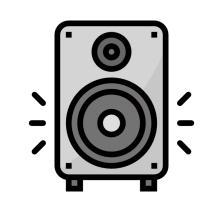
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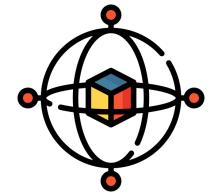
Produce a signal of a frequency scan (chirp).

Play the signal via speakers in proximity to the motion sensor.

Look for anomalies in the output of the motion sensor or the behavior of the containing device and identify the resonant frequency.





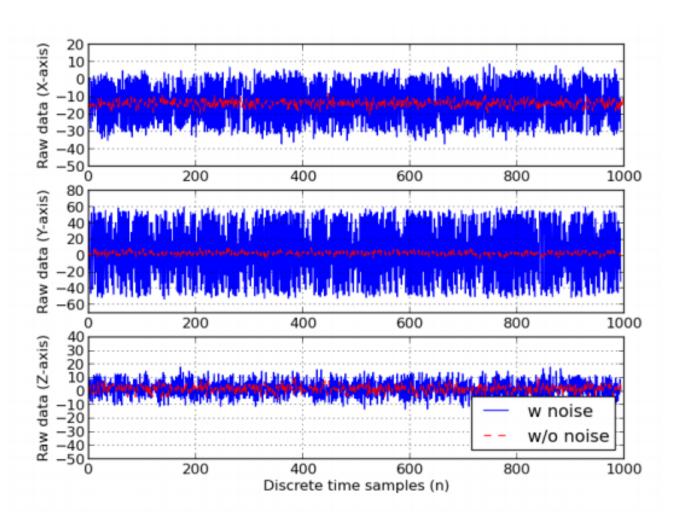






What are the anomalies that attackers need to look for when they apply the resonant acoustic injection frequency attack?

The picture on the right side shows how the original output of a gyroscope (in red) was changed in response to the attack (in blue)

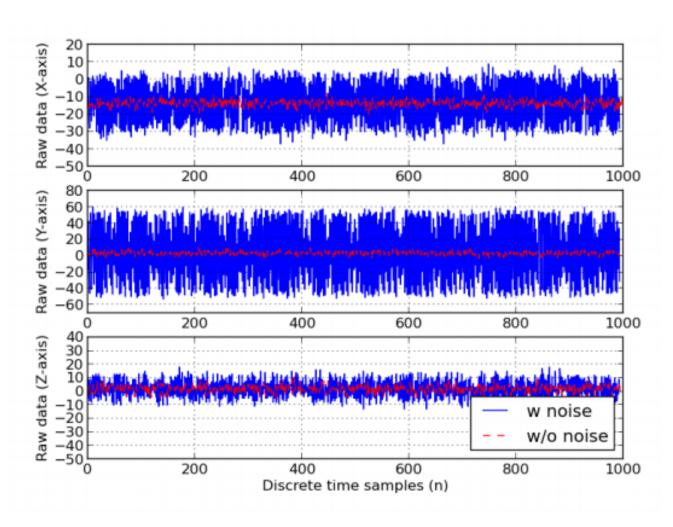


(d) Raw data samples of one L3G4200D chip with the single tone sound noise at 8,000Hz

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In some cases, the attack increases the output's:

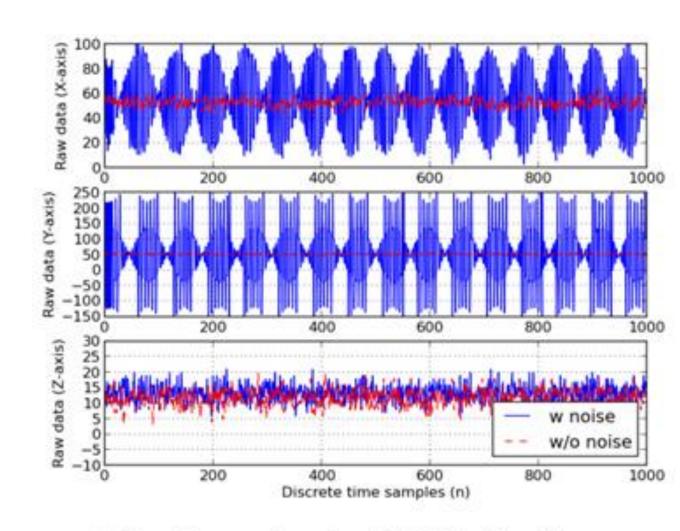
- Standard deviation
- Range
- The absolute minimum/maximum values



(d) Raw data samples of one L3G4200D chip with the single tone sound noise at 8,000Hz

Resonant Acoustic Injection Frequency Attack

In other cases (as can be seen in the picture on the right), the attack completely distorts the original signal.

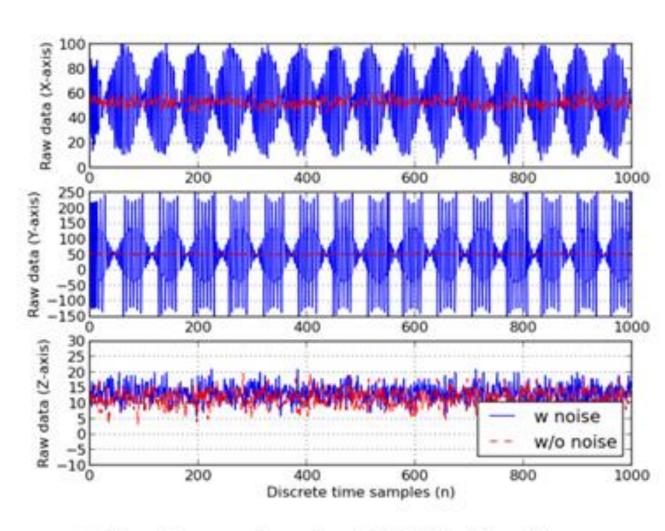


 (a) Raw data samples of one L3GD20 chip with a single-tone sound noise at 20,100Hz

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By applying the attack, attackers can control the output of a motion sensor.

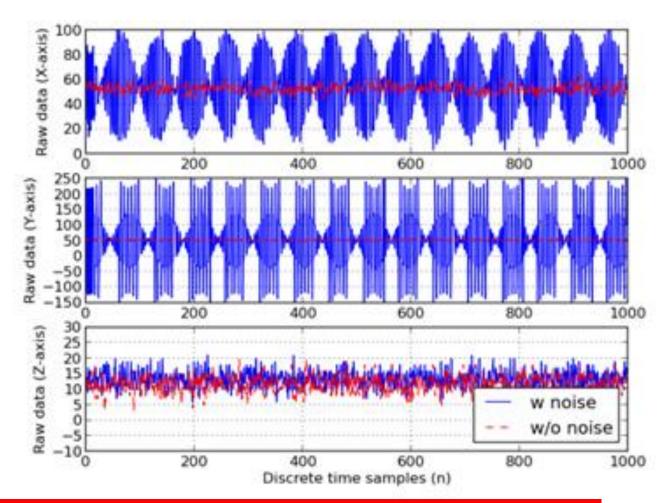


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Resonant Acoustic Injection Frequency Attack

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By applying the attack, attackers can control the output of a motion sensor.



These results clearly show that attackers can spoof the output of a target motion sensor, and affect the algorithms that rely on the motion sensor output.

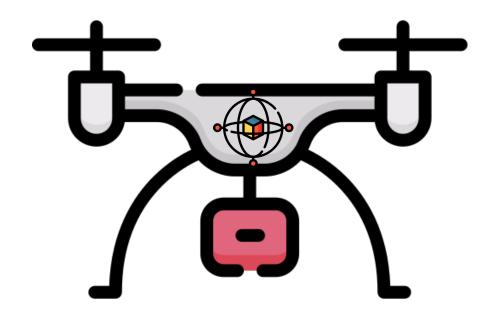
Question



Question: Given that the resonant frequency of a motion sensor is known, what are the risks that the resonant acoustic injection frequency attack poses to devices?

Gyroscope are integrated in drones' IMUs.

The drone is a real-time system that continuously uses a gyroscope's measurements to stabilize itself while flying:



While (true){

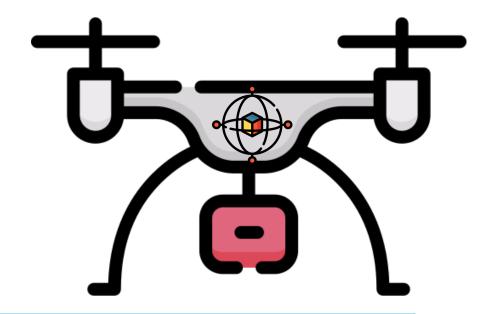
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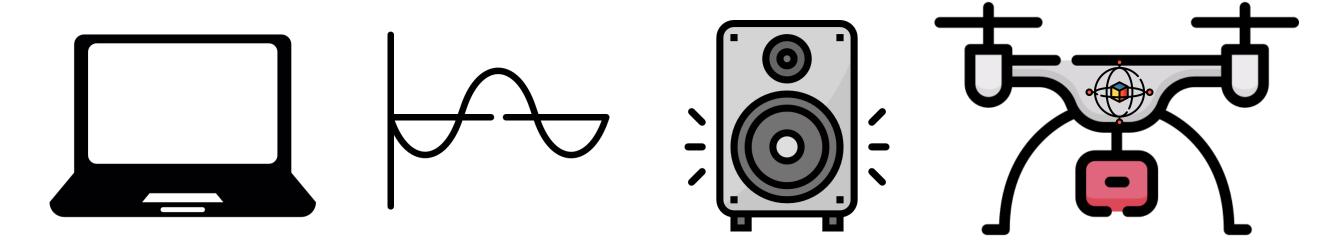
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This procedure is executed a few times on each second by a drone's OS

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By applying the resonant acoustic injection frequency attack against drones, attackers were able to apply a DoS attack: (1) preventing a drone on the ground from ascending, and (2) crashing a flying drone.

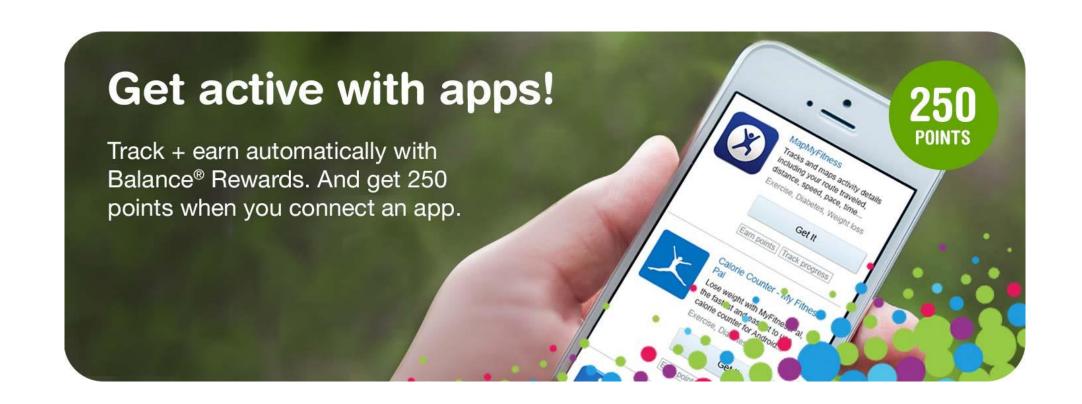


Accelerometers are integrated in smartwatches and fitness trackers.

Accelerometers are used to track many of the activities performed by the user, e.g., step counting.

Many companies incentivize people to exercise by offering reward programs tied to their personal fitness tracking wristbands.

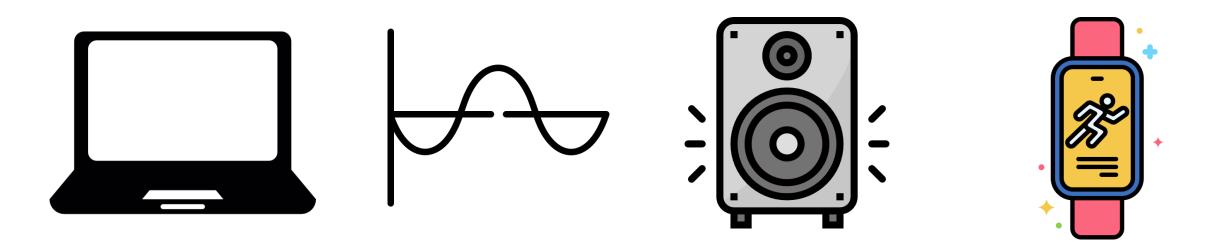




A user can earn free points by reaching a daily target of steps.

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By applying 40 minutes of the resonant acoustic injection frequency attack against the fitness tracker, attackers were able to register 2,100 steps and earn 21 reward points on Higi.com without taking a single step.

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Conclusions:

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The good news: In some cases, the attack is not considered a practical threat (e.g., crashing a flying drone used for deliveries) because it is hard to apply the attack from great distances.

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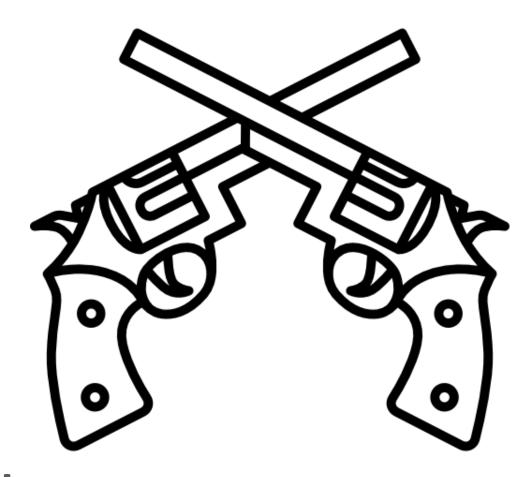
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The good news: In some cases, the attack is not considered a practical threat (e.g., crashing a flying drone used for deliveries), because it is hard to apply the attack from great distances.

The bad news: In other cases, the attack is considered a practical threat (e.g., spoofing the step counter of a smartwatch), because attackers can attack their own devices.

The Ugly



Privacy of Individuals

Privacy Issues in Smartphones and Smartwatches

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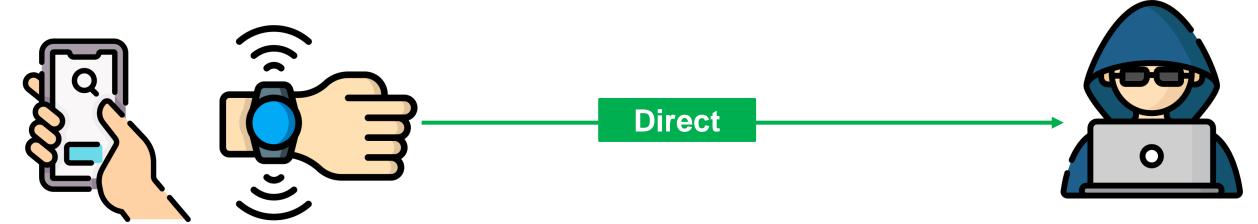
Smartphones and smartwatches are carried almost 24/7 by their users.



Question: How can attackers obtain motion sensor data?

Threat Model

There are two ways that attackers can obtain motion sensor data:

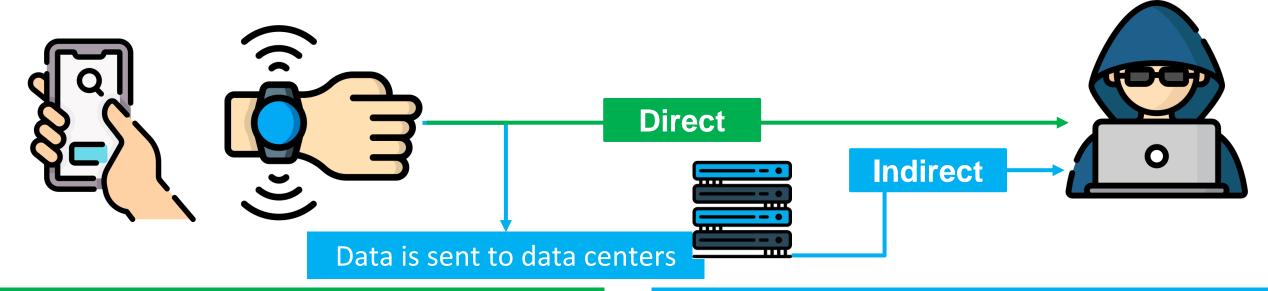


Attackers can obtain data directly from these devices

- By sampling the motion sensor via the browser when a user visits a compromised website.
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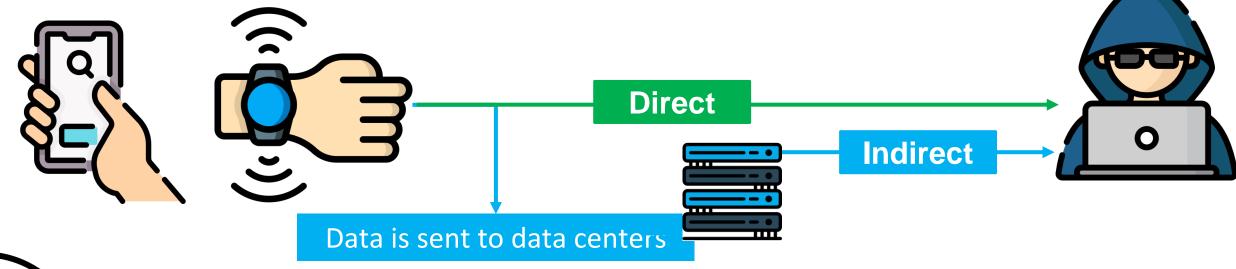
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Attackers can obtain data indirectly

• By hacking a legitimate application's data center.

Threat Model

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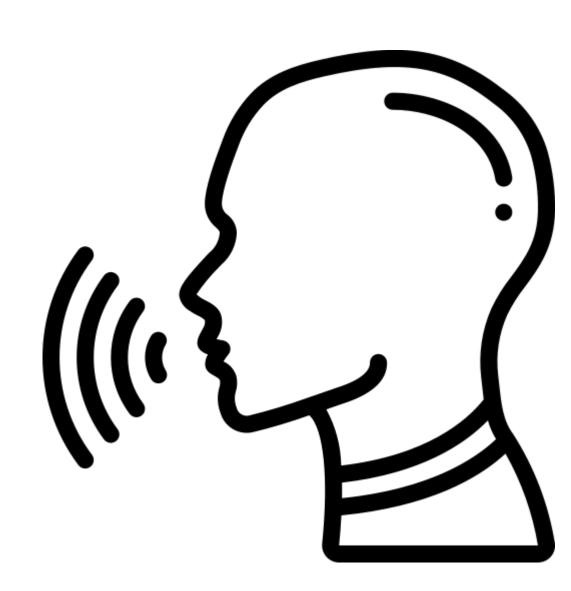


Question: Assuming that attackers were able to obtain motion sensor data, what are the risks that this data poses to individuals?

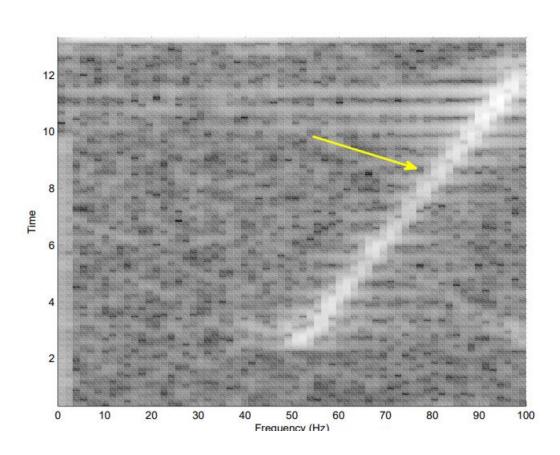
Case study 1



Question: Can motion sensors data be used to recover speech?

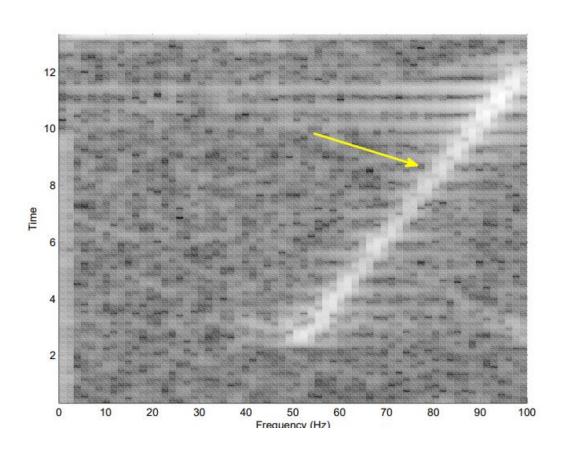


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In 2014, the attack was considered impractical:

A smartphone OS limits the sampling rate from the gyroscope to 200 Hz.

As a result, the accuracy of the model (KNN) was only slight better than a random guess.

The attack vector relied on a very loud speech

Practicality

Gyrophone [5]

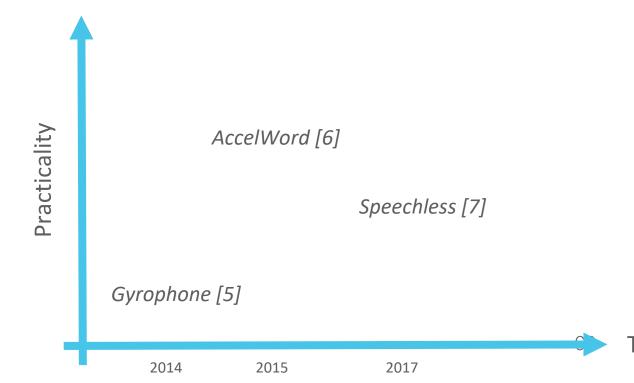


During the last seven years, the practicality of the method has improved significantly:

2015 to 2018 – Increased understanding regarding this attack vector was gained.

1st insight: MEMS accelerometers are more sensitive to acoustics than gyroscopes.

2nd insight: The effect of acoustics on motion sensors is increased when the smartphone and the speakers share the same physical surface.



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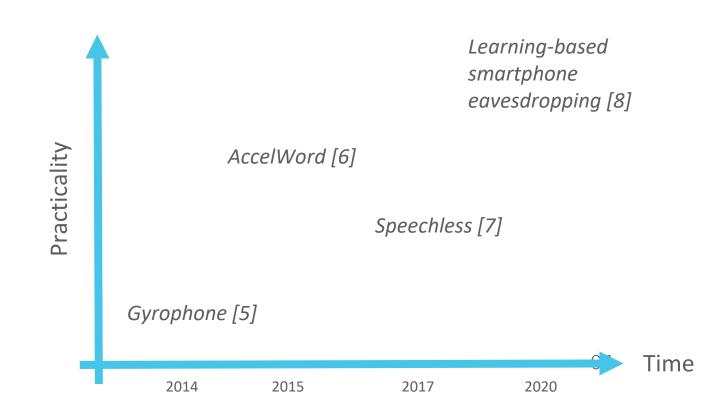
2015 to 2018 – Increased understanding regarding this attack vector was gained.

2020 – The attack vector was improved to make it a real and practical threat to privacy.

Some smartphones allow a sampling rate of 500 Hz.

Neural networks were used to classify words instead of the KNN approach. This yields excellent accuracy.

The attack vector relies on speech at a normal volume.



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Some smartphones allow a sampling rate

Learning-based smartphone eavesdropping [8]

2020

AccollMard [C]

2015

If smartphones manufacturers will allow a greater sampling rate of the integrated motion sensors in the future, we might even face a greater problem (i.e., a complete sound recovery of the speech rather than classification of isolated words with preliminary dictionary).

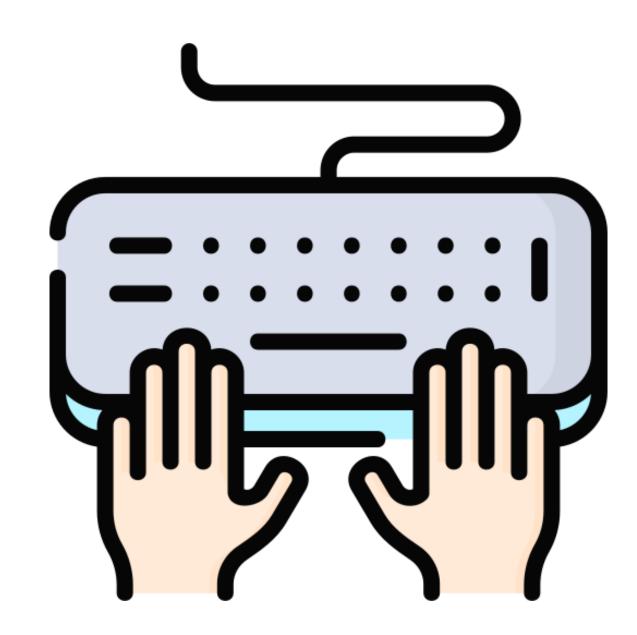
a normal volume

2017

Case study 2

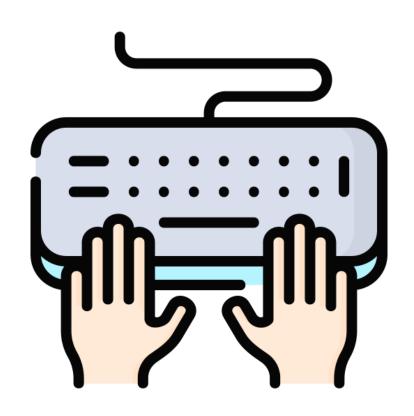


Question: Can motion sensors data be used for keylogging?



Keylogging

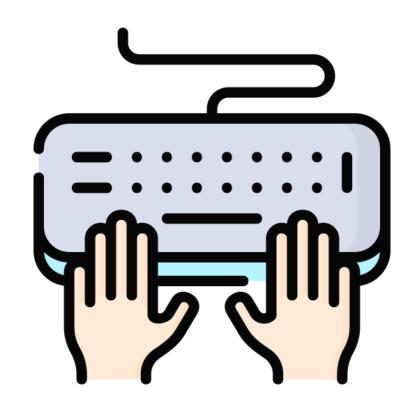
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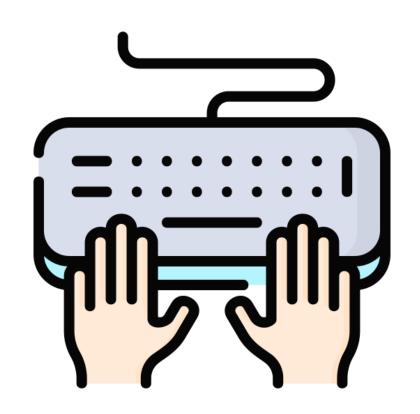
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Keylogging

Keylogging is the process of recovering the typed text or password from data.

Various methods were already suggested to create keyloggers.



Keylogging is usually done by analyzing data (e.g., acoustic data obtained from microphones) influenced by the side effects of typing.

If a user wears a smartwatch while typing on a keyboard, we expect the data from the motion sensors to indicate the movement of the wrist on the keyboard.



If a user wears a smartwatch while typing on a keyboard, we expect the data from the motion sensors to indicate the movement of the wrist on the keyboard.



Attackers need to overcome a primary challenge:

Missing information: Assuming that the user wears the smartwatch on his/her left hand, attackers can only recover the characters on the left side of the keyboard.

How can attackers fill in the missing gaps [9],[10],[11]?

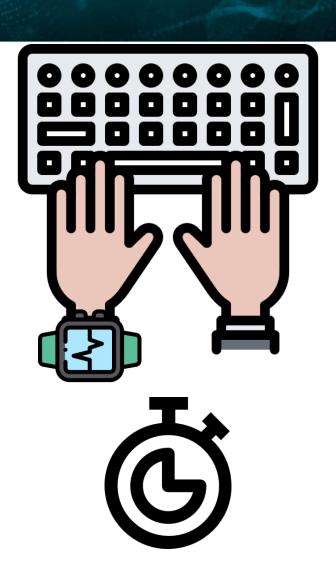
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Attackers can identify missing strokes on the right side of the keyboard by analyzing the motion sensor signal in the time domain to identify gaps and infer the number of missing characters.

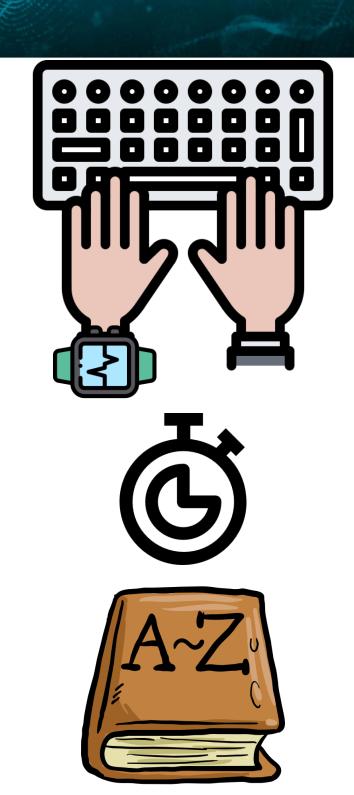


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Attackers can identify missing strokes on the right side of the keyboard by analyzing the motion sensor signal in the time domain to identify gaps and infer the number of missing characters.

Attackers can use a statistical model to fill in the missing characters using a dictionary.



How can attackers fill in the missing gaps [9],[10],[11]?

Attackers can detect strokes on the left side of the keyboard by analyzing data from motion sensors.

Attackars can identify strokes on the right side



This approach was implemented in various studies [9-11], showing good accuracy in recovering typing.

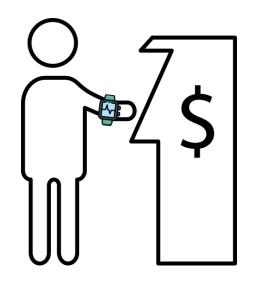
Conclusions:

Keylogging of the QWERTY keyboard via a smatwatch's motion sensors is quite practical.

The same approach can be used to recover text typed on a smartphone's touch screen keyboard.

Keylogging of PIN codes via a smatwatch's motion sensors is only possible if the user uses the hand with the smartwatch to press the buttons.



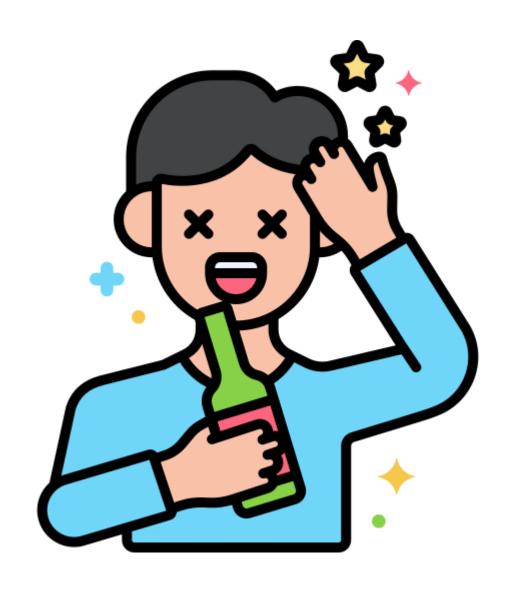


Recovering Sound from Motion Sensors

Case study 3



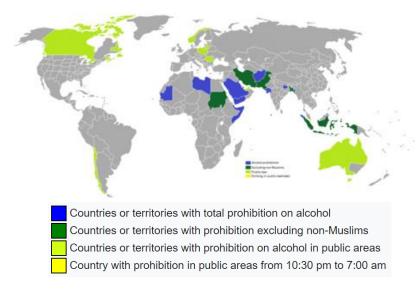
Question: Can motion sensors data be used to detect whether an individual was intoxicated?



The risk to individual's privacy:

Primary: In some Muslim countries around the world intoxication is prohibited by law, and governments penalize citizens for violating this law.

Secondary: This approach can be used to learn about another individual's habits (e.g., by parents or bosses).





Question: Assuming that a party was able to obtain an individual's motion sensor data, can the data be used by that party to determine whether the individual was intoxicated or not?

Police officers are trained to identify an intoxicated individual based on their gait (walk and turn test).



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This sobriety test has been used by police officers many years.

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Question: Can we identify whether a person is intoxicated by analyzing motion sensor data obtained from an individual's smartphone and smartwatch during free gait?

We performed a case study in order to answer this question, and the findings are described in the following paper:

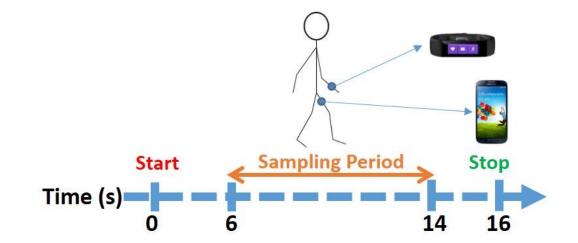
"The Age of Testifying Wearable Devices: The Case of Intoxication Detection" [12]

Ben Nassi, Prof. Lior Rokach, and Prof. Yuval Elovici.

The experiment:

The experiment took place at three different bars

Thirty individuals participated in the experiment.



Each individual was asked to walk twice with a smartwatch and smartphone for 16 seconds (only eight seconds of the motion sensor data was used):

The first walk took place before the individual started to drink

The second walk took place after the individual completed to drink.

The second time, we measured the breath alcohol concentration of each of the participants with a professional breathalyzer.

Feature Engineering:

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The second vector was extracted from the data obtained after the individual completed to drink.

The vectors consist of the exact same features: (a) statistical features, (b) distribution in the time domain, (c) distribution in the frequency domain, and (d) known gait features.

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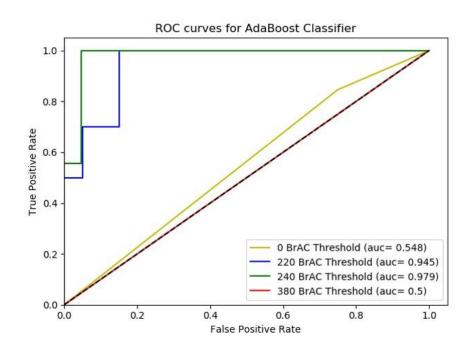
We ended up with 30 vectors (one for each participant) that indicate the difference in a person's free gait labeled by their breath alcohol concentration level.

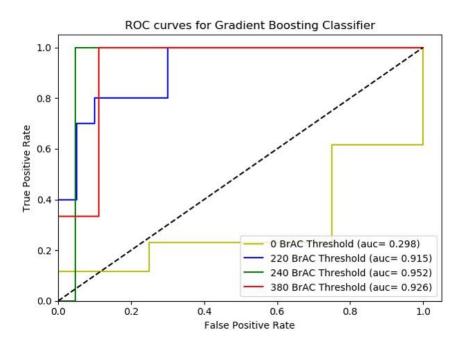
Results

We examined whether an individual's intoxication level can be determined for various BrAC levels (0, 220, 240, 380).

We compared the results of two ML algorithms: Gradient Boosting Classifier and AdaBoost classifier.

We found that our models can identify intoxicated individuals with a BrAC > 220 with a AUC > 0.91.





Results

The models are not perfect.

They each have FP and FN detections.

In some cases we cannot tolerate a specific type of mistake, and we want to evaluate the model's performance with respect to various policies.

	Predicted							
	0		220		240		380	
	Drunk	Sober	Drunk	Sober	Drunk	Sober	Drunk	Sober
Drunk	1	3	8	2	9	0	0	3
Sober	4	22	3	17	1	20	0	27

Table 3: Confusion matrices of the AdaBoost for BrAC thresholds of 0, 220, 240, and 380.

	Predicted							
	0		220		240		380	
	Drunk	Sober	Drunk	Sober	Drunk	Sober	Drunk	Sober
Drunk	1	3	6	4	9	0	0	3
Sober	4	22	1	19	2	19	0	27

Table 2: Confusion matrices of the Gradient Boosting Classifier for BrAC thresholds of 0, 220, 240, and 380.



Is it possible to tune the model to detect all intoxicated subjects?

This can be accomplished by:

Setting the model's TPR at 1.0 and analyzing how this affects the FPR, considering, e.g., how many sober individuals are misdetected as a result.

In general, we found that the FPR remains very low.

	Thresholds				
	0	220	240	380	
GBC	1	0.3	0.09	0.11	
AdaBoost	1	0.15	0.04	0	

Table 4: Detecting all intoxicated subjects: FPR (false positive rate) of classifiers with a fixed TPR (true positive rate) of 1.0.



Is it possible to tune the model so that all individuals detected as intoxicated by the model are actually intoxicated?

This can be accomplished by:

Setting the model's FPR at 0 and analyzing how this affects the TPR, considering, e.g., how many intoxicated individuals are missed as a result.

In general, this policy can result in many errors.

	Thresholds				
	0	220	240	380	
GBC	0	0.4	0	0	
AdaBoost	0	0.4	0.55	0	

Table 5: Detecting an intoxicated instance with no errors: TPR (true positive rate) of classifiers with a fixed FPR (false positive rate) of zero.

The primary risk that motion sensors currently pose is to individuals' privacy (rather than posing a threat to device security).

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Many people don't consider data from motion sensors a privacy risk, however attackers can derive various insights about users by analyzing motion sensor data:

Recovering speech

Keylogging

Detect whether an individual is intoxicated

Alternative way to locate a user (instead of GPS)

User identification

The primary risk that motion sensors currently pose is to individuals' privacy (rather than posing a threat to device security).

Many people don't consider data from motion sensors a privacy risk, however attackers can derive various insights about users by analyzing motion sensor data.

Currently, the most practical way to obtain motion sensor data requires the attacker to install an application on an IoT device in order to obtain motion sensor data.

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Many people don't consider data from motion sensors a privacy risk, however attackers can derive various insights about users by analyzing motion sensor data.

Currently, the most practical way to obtain motion sensor data requires the attacker to install an application on an IoT device in order to obtain motion sensor data.

However, we expect that ongoing external changes (adoption of 5G, increased commercial interest in motion sensor data) will result in increased data collection by third parties. As a result, we believe that in the near future, obtaining motion sensor data via third parties will become more practical than installing a malicious application.

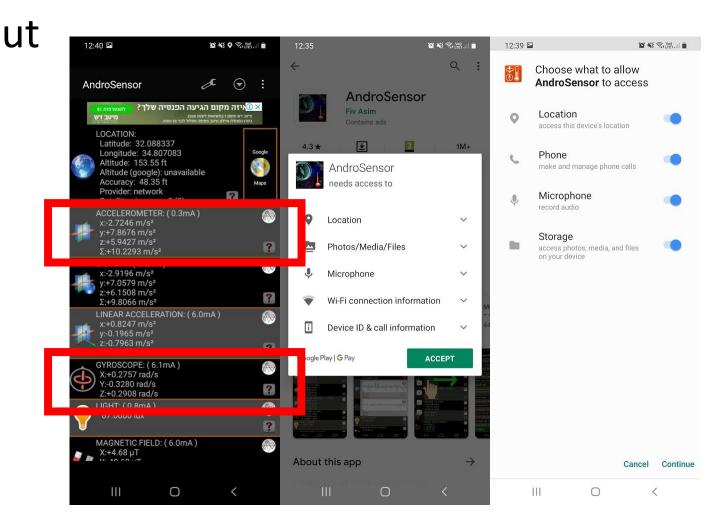
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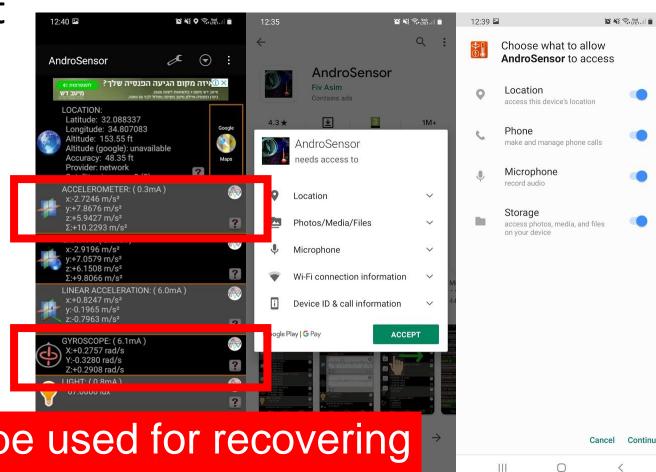
Currently, the most practical way to obtain motion sensor data requires the attacker to install an application on an IoT device in order to obtain motion sensor data.

We believe that ongoing external changes (adoption of 5G, increased commercial We believe that the common threat model to obtain motion sensor data is about to be change in the near future due to external changes.

Considering our understanding about the privacy risks associated with motion sensor data, we are quite surprised that such data can be obtained without user permission.



Considering our understanding about the privacy risks associated with motion sensor data, we are quite surprised that such data can be obtained without user permission.



A user's motion sensor data might be used for recovering speech and the user won't suspect at all.

Last point to think about:

Throughout the entire talk, we considered the fact that deriving insights about a user by analyzing the collected motion sensor data is a violation of the user's privacy.

This is true from a user perspective.



What about the bigger picture?

In a few well-known cases, a user's motion sensor data was used to:

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Contradict a husband's report of his wife's time of death, which changed the course of the investigation by enabling the police to prove that she was walking around an hour after her husband told the police she was shot by an invader.

A Fitbit Helped Police Arrest A Man For His Wife's Murder

The fitness tracker recorded the woman moving around her house for an hour after her husband told police she was shot by a home invader.



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Contradict a husband's report of his wife's time of death, which changed the course of the investigation by enabling the police to prove that she was walking around an hour after her husband told the police she was shot by an invader.

Charge a woman with false reporting after her Fitbit contradicted her rape claim by proving that she was actually walking around at the time in question.

A Fitbit Helped Police Arrest A Man For His Wife's Murder

The fitness tracker recorded the woman moving around her house for an hour after her husband told police she was shot by a home invader.



Woman Charged With False Reporting
After Her Fitbit Contradicted Her Rape
Claim

By Sophie Kleeman



In a few well-known cases, a user's motion sensor data was used to:

The answer to the question of whether we by want to allow a party to analyze an individual's motion sensor data, depends on the usecase.

The come usecases this can halp the police to also Reporting

In some usecases, this can help the police to solve crimes.

actually walking around at the time in question.

cted Her Rape



Thank You

Questions (



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