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Avoid Touching Your Face: A Hand-to-face 3D Motion Dataset (COVID-away) and Trained Models for Smartwatches

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CONFIRM's Vision – Fundamentally Transform Industry to a Smart Manufacturing Ecosystem

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Introduction

- Widespread of coronavirus (COVID-19) resulted in a global pandemic.
- Majority of the people own a wearable device such as health/fitness bands or smartwatches.
- Wearables + ? = Keep COVID-away by stopping the spread of germs.

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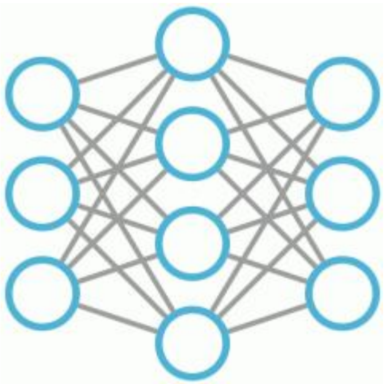

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We need to stop the spread of Severe Acute Respiratory Syndrome (SARS) like COVID-19, Swine flu, etc.

Problem 1

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Why we touch our faces so much, its hard to break the habit.

Ignoring hair in our eye or an itchy nose is ***easier said than done.*** We touch our face very frequently to,

- ✓ Scratch an itch.
- ✓ Soothe down when stressed.
- ✓ Touch during body-focused repetitive behaviors, etc.

Even medical students trained in infectious disease prevention ***touched their faces 23 times an hour*** during a lecture.

Problem 2

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Factory workers are facing a major COVID-19 risk.

Our hands are clean only until we touch the next surface. In many work environments such as manufacturing plants,

- ✓ Factory workers work collaboratively over an assembly line.
- ✓ Frequently touch the same products or surfaces repeatedly.
- ✓ Whenever a product or surface is contaminated by a virus, many workers get their hands contaminated.
- ✓ If workers touch their face with the contaminated hands, there is a high risk of viral disease spread.

COVID-away Introduction

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COVID-away Models

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COVID-away dataset trained models for wearables to help avoid people touching their face.

- We collected a hand-to-face multi-sensor 3D motion dataset and named it ***COVID-away dataset***.
- Using our dataset, we trained models and named it ***COVID-away models.***
- Our models continuously monitor hand movements to warn hands are moved (unintentionally) towards their face.
- Our models can be easily integrated into an app for smartwatches or fitness bands.

COVID-away Data Collection Process

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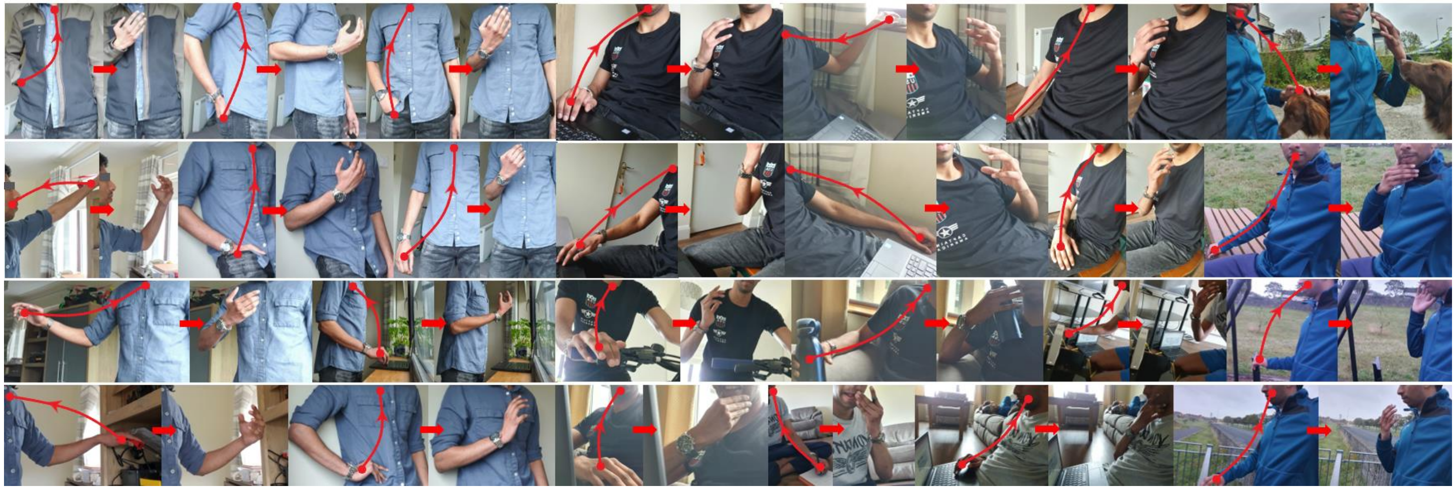

Collecting data for COVID-away dataset.

- We recorded sensor data for hundreds of dynamic hand-to-face movements in our ***COVID-away dataset*** using 3 volunteers.

- Our dataset contains data for such **2071** hand-to-face movements, with various postures (standing, leaning, slouching, etc.) and wrist orientations (variations in Roll, Pitch and Yaw).

COVID-away Dataset Structure

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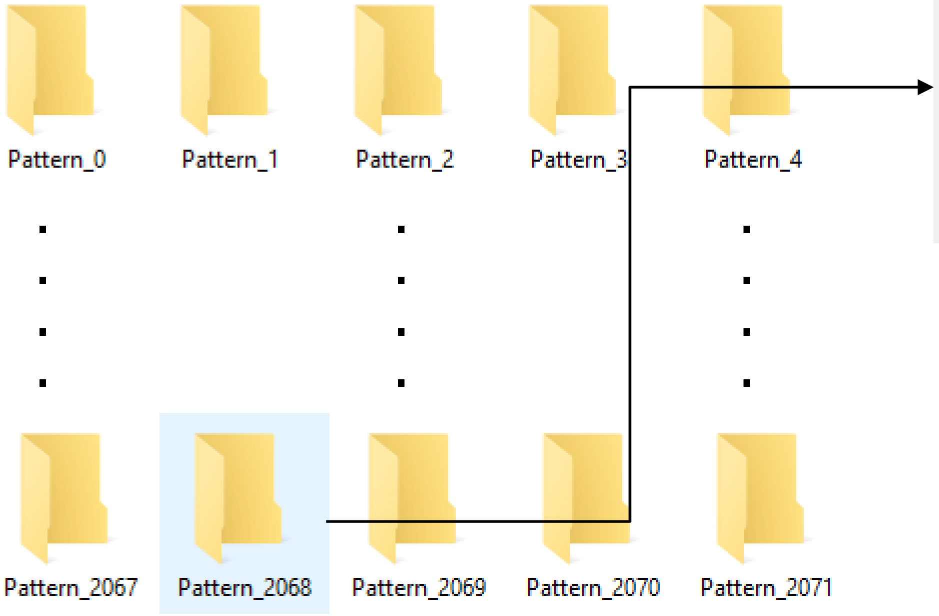

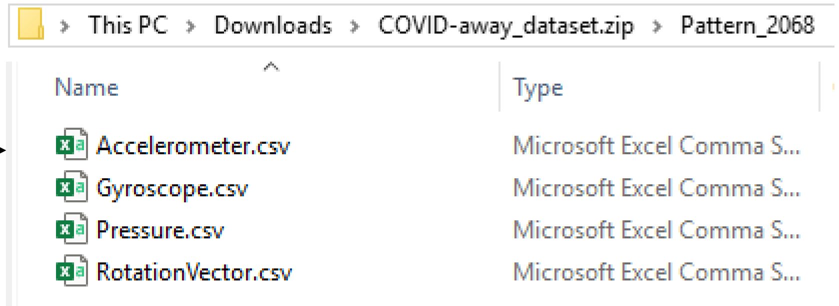

- Accelerometer.csv - Recording of acceleration in 3 axes.
- Gyroscope.csv - Rate of rotation (rad/s) around 3 axes.
- Pressure.csv - Change in air pressure (Millibars).
- RotationVector.csv - Unit-less (quantity) rotation-vector.

COVID-away Data Pattern Analysis

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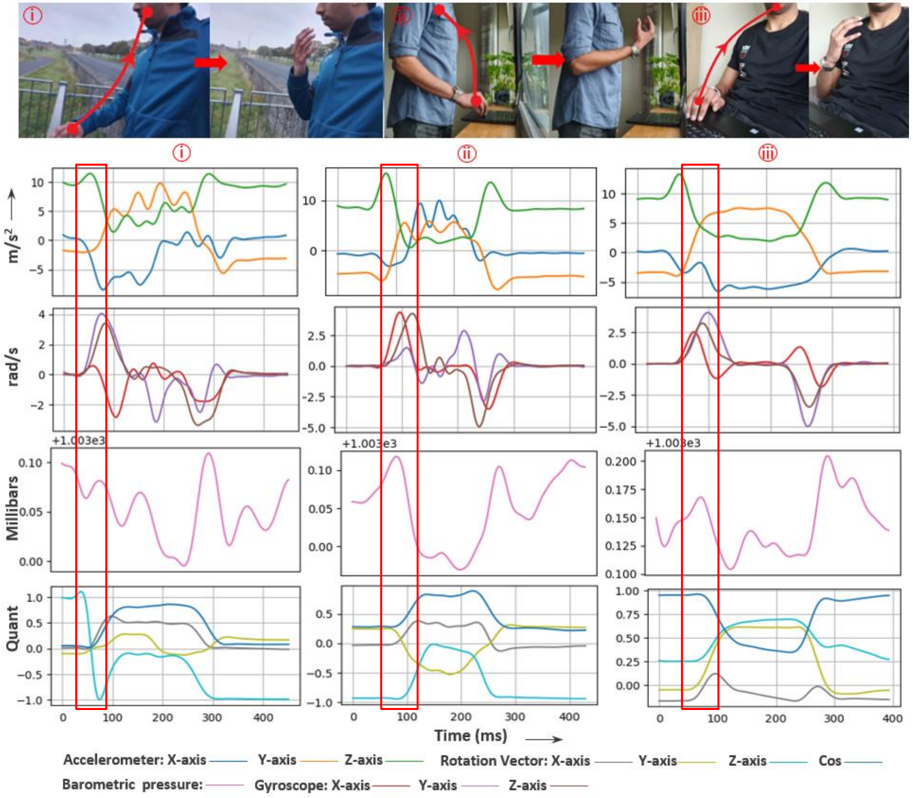

Sensor data correlation.

- We show data patterns recorded for three shown hand-to-face movements.
- Our dataset is **decently balanced** since roughly a similar number of sensor data patterns were recorded by three different volunteers.
- Total 2071. 708 patterns from the first, 672 from the second, 691 from the third.

COVID-away Features Extractor

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Function	Description
mean	Mean value
std	Standard deviation
mad	Median absolute value
energy	Average sum of the squares
correlation	Correlation coefficient
iqr	Interquartile range
skewness	Frequency signal Skewness
entropy	Signal Entropy
arCoeff	Autoregression coefficients
kurtosis	Frequency signal Kurtosis

Feature vectors to compute for all the 2071 patterns.

- Our feature extractor computes the **feature vectors** shown in Table, for our dataset.
- A total of **102 features** were extracted to describe one hand-to-face movement.
- We use these extracted features to train models (COVID-away models) that instantly warn the users before they touch their face.

COVID-away Models Design

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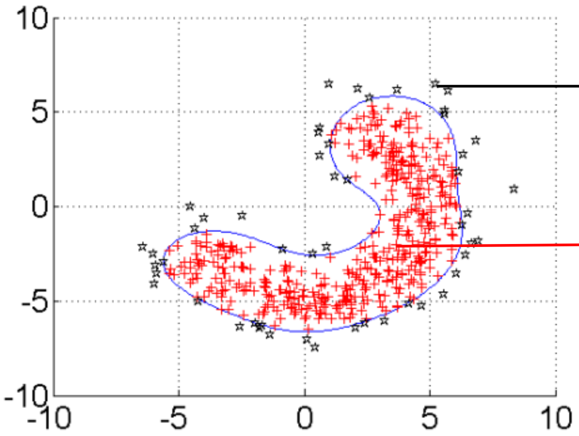
COVID- away models for realtime warnings

- Our models should classify the type of motion using < 70 % data i.e. before hand touches face.
- If a sudden acceleration is noticed along any of X, Y & Z axes we consider it as start of motion.
- Then we start feeding the sensor data to our **COVID-away models** for real-time hand-to-face motion classification result-based alerts.

COVID-away OCC Models

Our use-case is a binary classification problem since we have only one activity (hand-to-face movement) to detect. We apply,

- ✓ One-Class Support Vector Machines (OC-SVM).
- ✓ Isolation Forest (iForest).
- ✓ Minimum Covariance Determinant (MCD).
- ✓ Local Outlier Factor (LOF).



We use OCC because we only have the majority class (features for hand-to-face movement) data for training.

Practically not feasible to collect outliers since thousands of non-hand-to-face movements exist.

OCC Models Performance

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Training Data	LOF			MCD			iForest			OC-SVM		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Acc	1.00	0.49	0.65	1.00	0.87	0.93	1.00	0.79	0.88	1.00	0.75	0.86
ACC+Gyro	1.00	0.50	0.66	1.00	0.79	0.88	1.00	0.77	0.87	1.00	0.73	0.85
Acc+Gyro+ Mbar	1.00	0.49	0.65	1.00	0.77	0.87	1.00	0.77	0.87	1.00	0.75	0.86
Acc+Gyro+ Mbar+Rvect	1.00	0.49	0.65	1.00	0.79	0.88	1.00	0.79	0.88	1.00	0.75	0.86

Evaluating COVID-away one-class classification models.

- We recorded 100 new motion patterns for both hand-to-face & non-hand-to-face motion using a **new fourth volunteer**. Used this fresh data for evaluation.
- OCC models were able to accurately classify all the hand-to-face movements (Precision 1), but the F1-score slightly dropped due to the reduced Recall value.
- The MCD model produces the highest F1-score (0.93) just using the accelerometer data.

COVID-away CNNs

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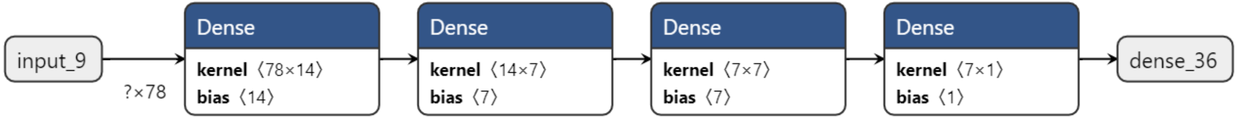

COVID-away CNN Architecture.

- Even with less training data, we obtained reasonable performance because,
- We teach the CNNs that deviations from the 2071 data patterns are deemed as outliers (non-hand-to-face movements).
- We trained two CNNs. The first requires only Accelerometer data (Acc = 39 features) to detect hand-to-face movement.
- The second model requires real-time data from two sensors for detection (Acc+Gyro = 78 features).

CNN Size & Latency Optimization

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- To produce a smartwatch friendly version of the COVID-away CNNs, we optimize it by quantizing both its weights & activations to INT-8. Hence the convolutions of CNN-Opt takes the following form:

$$\psi(w,x) = 2^{-2(Q-1)} \sum_{i \epsilon D} W_i X_i \doteq 2^{-2(Q-1)} . \phi(W,X)$$

D is the number of input channels.
ψ is CNN's convolution operation.
$\phi\ (W\ ,\ X)$ is an accumulator containing high precision values.

- Why Quantization,

  - ✓ INT-8 results in fast processing hence real-time warnings.
  - ✓ To lower power consumption.
  - ✓ To reduce model size.

COVID-away CNNs Performance

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Training Data	CNN					CNN-Opt				
	Size (KB)	P	R	F1	Lat (ms)	Size (KB)	P	R	F1	Lat (ms)
Acc	41.2	1.00	0.73	0.84	3.024	4.9	0.97	0.74	0.83	0.021
ACC+Gyro	47.7	0.92	0.86	0.89	3.403	3.8	0.92	0.85	0.89	0.029

Evaluating COVID-away CNNs & its optimized versions (CNN-Opt): Performance, size & latency (Lat) comparison.

- We noticed performance improvements with increased features.
- But beyond 78 features, the increase in the model's size & latency was higher, resulting in non-real-time warnings.

COVID-away Repository

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COVID-away dataset and models are freely accessible at: https://github.com/bharathsudharsan/COVID-away

	bharathsudharsan Update README.md	59fc269 on Sep 2	32 commits
2	COVID-away CNNs	Uploading the optimized models	2 months ago
1	COVID-away_dataset_visualization	Updated Readme	2 months ago
2	COVID-away_one-class_classification_...	Update README.md	2 months ago
3	Features Extractor	Updated Readme	2 months ago
	README.md	Update README.md	last month

COVID-away Dataset: Enter a # between 0 - 2071, to obtain the visualization of that respective data pattern.

COVID-away Models: Contains trained models ready for smartwatch integration

Feature Extractor: Compute 102 features for each recorded hand-to-face motion data pattern.

Use case: Protecting Factory Workers

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M News › Irish News › Coronavirus Ireland

Offaly meat factory urged to close as midlands counties placed on lockdown following Covid spike

The spike in cases that prompted the restrictions in Offaly, Kildare and Laois have been linked to outbreaks in meat processing factories

COVID-away models are generally applicable to all settings.

- Similar to following other safety measures such as face-covering, social distancing, etc. we recommend asking each worker to wear our COVID-away model integrated fitness band.
- This new safety measure boost the confidence of employees to return to work since our models facilitates them to follow the ***key individual-level practice***.

Conclusion

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- We presented our COVID-away dataset and trained models.
- When any of our model is deployed on smartwatches, it can instantly warn the users when their hands are moved (unintentionally) to the face.
- MCD model showed the highest performance (0.93 F1-score) using just the accelerometer data.

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