# ShakeCast: Using Handshake Detection for Automated, Setup-Free Exchange of Contact Data 

Tim Weißker<br>Erdan Genc<br>Andreas Berst<br>Frederik Schreiber

Florian Echtler




An exemplary $y$-acceleration plot of a handshake from both participants. The red (outer) lines indicate start and end of the longest positive window streak; the blue (inner) line is the first local extremum within this extracted range


#### Abstract

We present ShakeCast, a system for automatic peer-topeer exchange of contact information between two persons who just shook hands. The accelerometer in a smartwatch is used to detect the physical handshake and implicitly triggers a setup-free information transfer between the users' personal smartphones using Bluetooth LE broadcasts. An abstract representation of the handshake motion data is used to disambiguate between multiple simultaneous transmissions and to prevent accidental data leakage.




The setup consists of two smartwatches, each paired with a corresponding smartphone. The accelerometer is used to detect a handshake and trigger a data exchange.


A perfect feature will have a minimal difference within in the set of matching and maximal difference within the set of non-matching instances.


Due to the large amount of noise present the handshake may fall into different bins than those used. To allow for some margin of error, multiple hashes are generated considering adjacent bins for each feature.

## I Peer-to-Peer Data Exchange

When a handshake was detected, the system exchanges contact data between the two smartphones. However, a single mobile device may receive contacts from people that the owner did not shake hands with. To address this issue, we derive a code which is used to hash the payload. Ideally, only the device with the matching handshake data can reconstruct this code.

## II Handshake Matching

To generate the same code for hashing on both devices, we need to determine features which behave similar. We considered the Fast Fourier Transformation (FFT) of the signal as most important set of features because of its time-invariant and noise-filtering properties. We found the features with the highest importance for disambiguation. Through a simple encoding scheme, a successful decoding step shows that these data are from one physical handshake.

## Performance Evaluation and Discussion

From a usability point-of-view, the worst case for the classifier would be a false negative, as the users would have to shake hands again to complete the exchange. Since only about $50 \%$ of all matching shakes fall into the same bin, an accepted bin difference of at least one should be chosen. False positives, on the other hand, could be reduced using additional non-feature-based approaches. Using only the two most salient feature $\mathrm{FFT}_{Y 2}$ and $\mathrm{FFT}_{Y 3}$ provides nearly $77 \%$ true positive and $79 \%$ true negative matches with allowing a bin difference of two and using a third feature FFT $_{x y z o}$ allows us to accept matches with $92.31 \%$ but with a reduced true negative rate of $66.32 \%$.

