Dop-NET: a micro-Doppler radar data challenge

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Radar sensors have a new growing application area of dynamic hand gesture recognition. Traditionally radar systems are considered to be very large, complex and focused on detecting targets at long ranges. With modern electronics and signal processing it is now possible to create small compact RF sensors that can sense subtle movements over short ranges. For such applications, access to comprehensive databases of signatures is critical to enable the effective training of classification algorithms and to provide a common baseline for benchmarking purposes. This Letter introduces the Dop-NET radar micro-Doppler database and data challenge to the radar and machine learning communities. Dop-NET is a database of radar micro-Doppler signatures that are shareable and distributed with the purpose of improving micro-Doppler classification techniques. A continuous wave 24 GHz radar module is used to capture the first contributions to the Dop-NET database and classification results based on discriminating these hand gestures as shown.

Introduction: Dop-NET is a newly developed shared dataset containing radar micro-Doppler signatures [1]. This Letter introduces what Dop-NET is, the goals of the dataset and baseline classification results on the data currently available. The first data to be released on Dop-NET is the radar measurements of human hand gestures. Gesture recognition using RF sensors is a growing area of radar research, as companies including Google [2] are starting to produce real devices that look to recognise hand movements with radar sensors.

Human–computer interaction (HCI) using dynamic hand gesture recognition is potentially an effective and natural method for a user to control a device. The hypothesis of the research in this area is that radar-based gesture recognition will be more effective than vision-based methods, because they are not susceptible to light conditions, and can detect and classify targets, providing rich Doppler information [3, 4]. A current disadvantage, in comparison to optical imagery, is that radar micro-Doppler data is much less common and more challenging to generate or access.

Image classification is a mature area of computer science and has benefited greatly from the creation of the ImageNet dataset [5], which enabled the rapid progression of image classification processing. The objective of Dop-NET is to enable the same rapid progression of classification algorithms that ImageNet facilitated within the radar signal processing community. Through the Dop-NET website the data is freely available as part of data classification challenges. Currently hand gesture data is available but further datasets of walking gait analysis, human actions (carrying items, falling, etc.) and bird/drone micro-Doppler will also be added. We believe that this shared database can become an effective tool for developing new and better machine learning and radar data understanding algorithms.

The database is organised in a hierarchy in which each node represents the data of a person which is divided in different gestures recorded from that person. The organisation has been based on the same concept as seen in ImageNet and WordNet [5, 6]. It contains data in the form of either range-time–intensity (RTI) or Doppler-time spectrogram complex matrices. Within the hand gesture dataset the subtrees are, persons A, B etc., and then the gesture measured.

Dop-NET characteristics: Dop-NET aims to gather significant number of radar recordings and provide them as a data classification challenge. This project is initiated with gesture recognition data but will look to extend beyond this. Currently, the dataset contains 3452 files (in the form of RTI and micro-Doppler spectrograms) measured from ten different people, using two types of Radars, continuous wave (CW) and frequency-modulated continuous wave (FMCW). The hand gestures that were recorded were a wave, click, swipe and pinch actions, as shown in Fig. 1.

The data is all labelled to allow supervised learning classification techniques to be applied. In the image recognition community when sourcing large datasets these can be unlabelled or mislabelled. Currently, this is not an issue within Dop-NET, but as it expands this may need to be addressed.

The hierarchy of Dop-NET is a series of subtrees which represent the data from different people, and then gestures. Those subtrees are divided into a data cube of the number of repeats of the four gestures. Data has been divided into training and test datasets, with the training fully labelled and the test datasets un-labelled but on submission of results the Future data releases will come with new branches of target and subtrees for more data challenges.

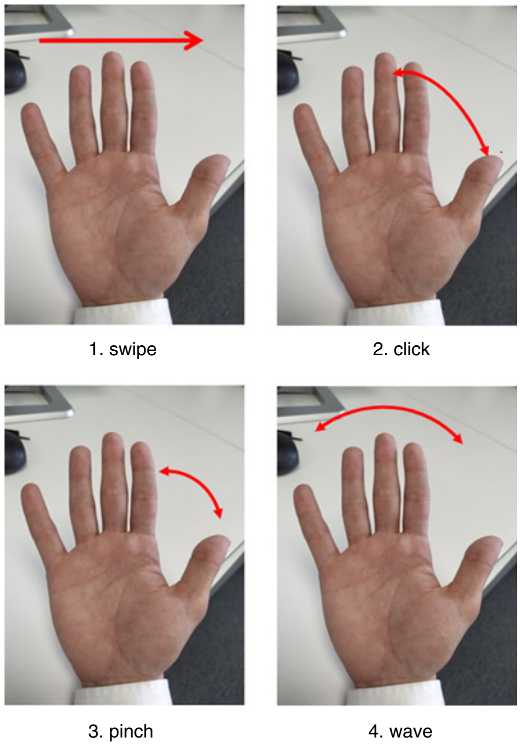

Fig. 1 *Gestures 1. Swipe; 2. Click; 3. Pinch; 4. Wave*

Diversity: So far we collected data from ten different people, and we recorded a diverse set of RTI data, Doppler-time spectrograms data of four different gestures, measured with two distinct radars (CW and FMCW). Initially, Dop-NET will release the FMCW data as a data challenge, but the CW data will then be released. When visually inspecting the gestures some differences, in the Doppler-time domain, are clear to see. The waving gesture has an oscillatory shape and longer duration. The click gesture happens over the shortest time frame (as a click is only a short sharp action). Then the pinch and swipe actions do show some level of similarity which could make them challenging for a classifier.

Accessibility: Furthermore, Dop-NET offers a comprehensive guide to use the Radar Data, in order to be accessible to researchers from the computer science community and beyond.

Datasets: Radar sensors have previously been successfully used to classify different actions such as walking, carrying an item, discriminating between people and animals gaits or drones and bird targets [7–11]. All of this analysis used the phenomenon called micro-Doppler which is the additional modulations generated by movements a target has on top of its bulk velocity. For example, a person may walk forwards at 3 m/s but as they move at this speed their arms and legs oscillate back and forth. This movement creates a signature, which was coined as micro-Doppler by researcher Chen *et al.* [12].

FMCW radars are popular, inexpensive and easy to use sensors that lend themselves well to the challenge of recognising human hand gestures. The data output is able to provide both the range and the Doppler signature of the targets detected within the beam of the sensor [13]. CW radars are also being considered as even more inexpensive sensors that could be used in this application and an additional dataset is being developed for release on Dop-NET for comparison with the FMCW measurements. The advantage of CW is the reduced cost and simplicity of the sensor but the disadvantages are that they cannot provide a range to the target that is being observed.

FMCW dataset: The ancortek radar system used to generate the dataset is a 24 GHz FMCW radar (with a 750 MHz bandwidth and a chirp period of 1 ms). The system has a standalone GUI to control and capture data or can be commanded within a Matlab interface to capture signals. The radar has one transmit antenna and two receive antennas, but only the co-polarised channel was used for the purposes of this dataset. Each gesture was made directly in front of the radar at a distance of ∼ 30 cm at the same height as the radar. The system was then initiated to capture for 30 s of data and the candidate repeated the actions numerous times within this window. Afterwards the raw data was then cut into individual gestures that occurred over the whole period. These individual gesture actions have varying matrices sizes, hence a cell data format was used to create a ragged data cube. The data that has been shared as part of this challenge was created by the following flow of pre-processing:

- Generate 2D matrices of slow versus fast time samples for each gesture.
- FFT samples to convert to the range domain, creating a range versus time intensity (RTI) matrix.
- Use a moving target indicator (MTI) filter to suppress static targets
- Extract range bins within the MTI data that contain the gesture movement for coherent summation.
- Generate a Doppler versus time 2D matrix by using a short-time Fourier transform (STFT) on the vector of selected samples (see Fig. 2).
- Store the complex samples of the Doppler versus time matrix within a larger cell array which is a data cube of the *N* repeats of the four gestures from each person.

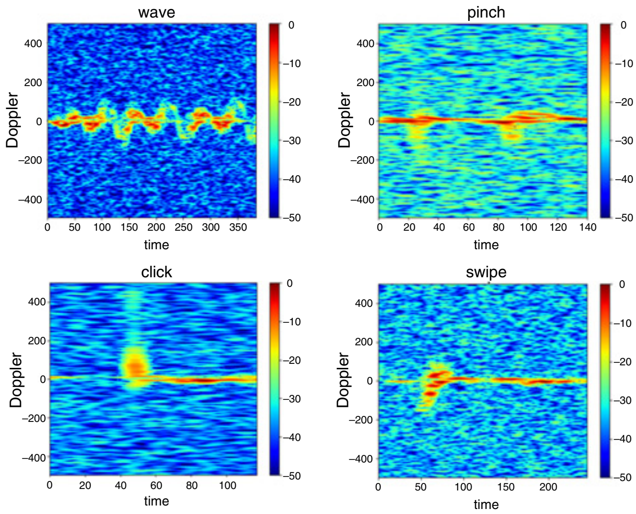

Fig. 2 *Individual spectrograms showing time versus frequency signatures four dynamic hand gestures performed by one participant. These were captured by 24 GHz FMCW radar*

The data is then stored in this format in order for it to be read in, features to be extracted and the classification process to be performed. This allows for research into which features should be extracted and what classification processes provide the best results using this shared dataset.

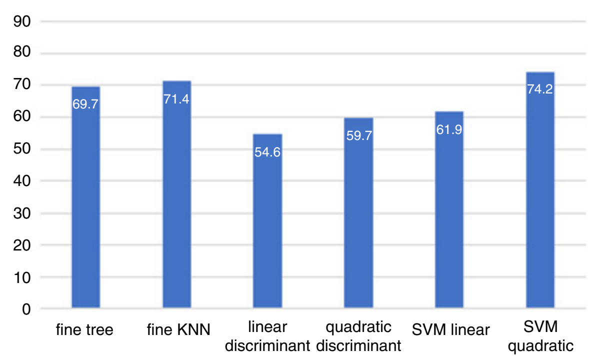

Fig. 3 *Classifier accuracy for six classifiers on Dop-Net.com dataset*

Multiple classifiers were then trained on the dataset of 3052 measurements which was split into a test set of 643 samples taken from across the five people leaving 2433 samples for training. Five features were extracted from each micro-Doppler spectrogram which were the mean, median, maximum, entropy and standard deviation. Six different classifiers were then used to estimate all of the gestures in the test set correctly and their results can be seen in Fig. 3. The classifiers used were the fine trees, K-nearest-neighbour, linear discriminant, quadratic discriminant, support vector machine (SVM) linear and SVM quadratic. From these simple features, the classification success rates were found to be relatively low for some of the classifiers, but this is the first baseline result with this dataset and we hope future research outputs for this data challenge will improve on these. The best accuracy of 74.2% was obtained using SVM quadratic classifier, although this required the longest computational time for training the model.

Data science challenge: The focus on the proposed radar data challenge is the classification of the 4 dynamic gestures. There has been a vast amount of research into various technologies use as HCI. This includes the Microsoft kinetic sensor, virtual reality wand controllers and even sensors that read a person's brain waves. Recently, Google has developed a small radar sensor called Soli which it proposed as a device for gesture recognition [2]. This research challenge proposes the use of a compact radar sensor as a device that can be used in HMI and has encouraged researchers to investigate the feasibility of a radar device in this role.

The format of the challenge is to read in the 'training' dataset, define a means of classifying each of the samples (neural network, simple SVM, exact manual features) and output a trained model. Then apply this model to the 'test' data and create a list of predicted classes for this. It is this predicted class list that is submitted along with the trained model as part of the participant's assessed submission to the challenge.

The training data that we share is a matrix of Doppler versus time signals from stored in a cell format. This is a labelled dataset that can be used to create a classifier model. A separate Matlab.m file is shared to show users how to read this data. The training data contains 2433 files. In addition a test dataset that is not labelled is also shared. The trained classifier the participants create can be tested against this data and their submission to the challenge will include their predicted classes. The test data contains 643 files. The data provided on the competition is available to download [1] and follow on publications are encourage to demonstrate new machine learning and classification techniques.

Exploitation of Dop-NET: The main goal of Dop-NET is to be mechanism for the release of large scale radar datasets for the research community to use. It is envisioned that the data released can be a training resource and a benchmark dataset. Currently, there is limited data available to the radar community and often kept within the research group/company that generates it, mainly due to IP issues. By creating a mechanism to share radar datasets we hope to produce a wider impact for the whole community. The work invested into Dop-NET will look to gather large and diverse radar datasets that will not only help to train new algorithms, but also make them more powerful.

Conclusion: This Letter has introduced the Dop-NET data challenge to the wider research community. The radar used the capture the data, the types of measurement and baseline classification results have been presented here. It is the goal of this work to enable more research groups to have access to real radar data in order to progress the field of radar micro-Doppler signal processing and classification. Currently the database is focused on hand gesture micro-Doppler signatures. In the near future this is planned to be expanded to micro-Doppler signatures of people walking, birds and small drones.

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One or more of the Figures in this Letter are available in colour online.

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