



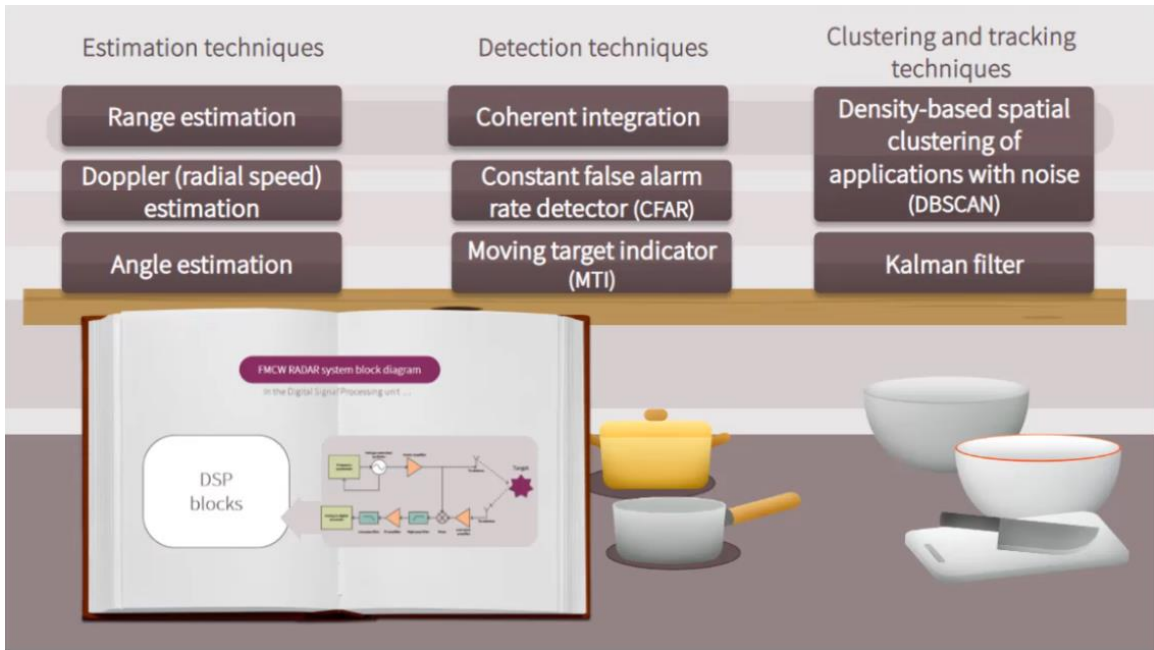
In order to use Infineon's RADAR environments the best way possible, it is not only important to know the basics of RADAR physics, but it is also beneficial to understand what is happening on the software side!

This is why we dedicate this training to the Digital Signal Processing (DSP) of Frequency Modulated Continuous Waves (FMCW)!

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In the Digital Signal Processing unit ...


...we find various blocks with different algorithms – just like you find various ingredients in the kitchen.

Depending on the recipe you want to cook, so which algorithm you need to apply, certain blocks are combined.

Let's start looking at the ingredients more closely!

Estimation techniques

Range estimation	$R_{max} = \frac{f_{b,max} c}{2 K}$	$\Delta R = \frac{c}{2BW}$
Doppler (radial speed) estimation	$v_r = \left[-\frac{\lambda}{4PRT}, \frac{\lambda}{4PRT} \right]$	$v_{res} > \frac{\lambda}{2N PRT}$
Angle estimation	$\theta < \sin^{-1}\left(\frac{\lambda}{2d}\right)$	$\theta_{res} > \frac{\lambda}{Md \cos \theta}$



We have covered the physics behind range, speed, and angle estimation in the video **RADAR basics**. But how are the physics signals being processed in FMCW mode?

Discover how each equation – based on fast Fourier transformation (FFT) – is formed in order to understand the DSP algorithms better.

Click on the buttons to explore.

Click on the buttons to discover how each equation – based on Fast fourier transformation (FFT) is formed in order to understand the Digital Signal Processing algorithms better.



Let's now focus on range estimation.

The maximum range the RADAR chip detects depends on the application.

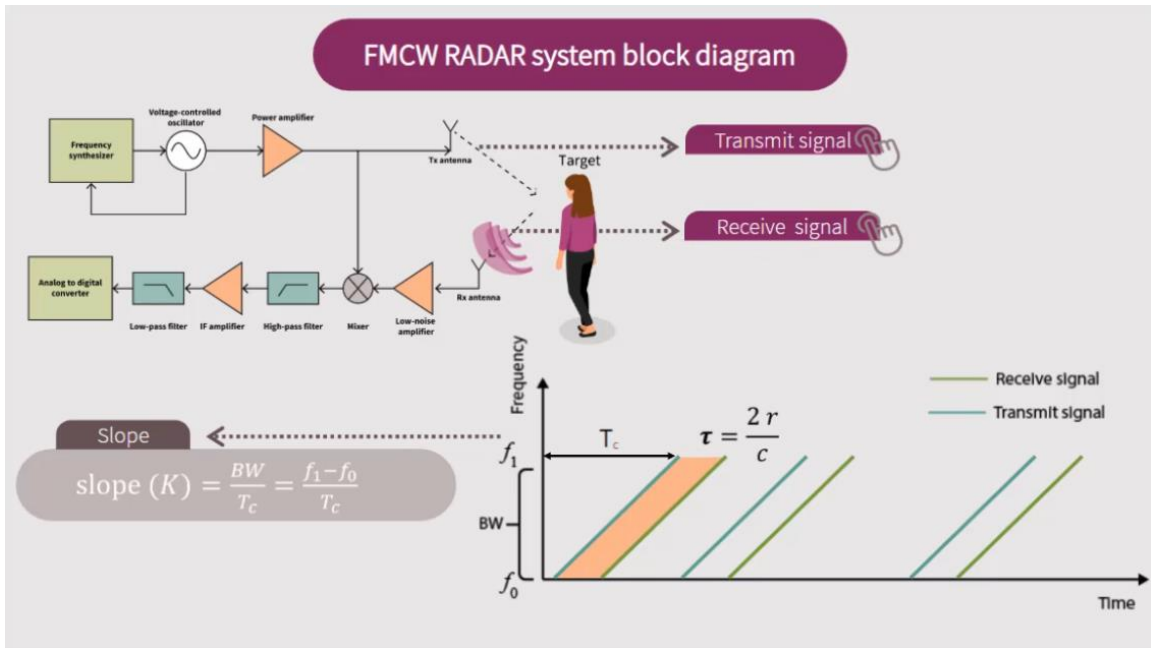
But what is behind the maximum range equation?

Let's look into this by taking the example of presence detection.

Whether you mount the RADAR chip as a standalone device onto the wall or whether it is implemented inside a smart TV, you will want to detect objects inside the room up to a certain distance, the so-called maximum range.

But you also want to be able to detect several objects at the same time and distinguish them from each other along the range plane, in a certain range resolution.

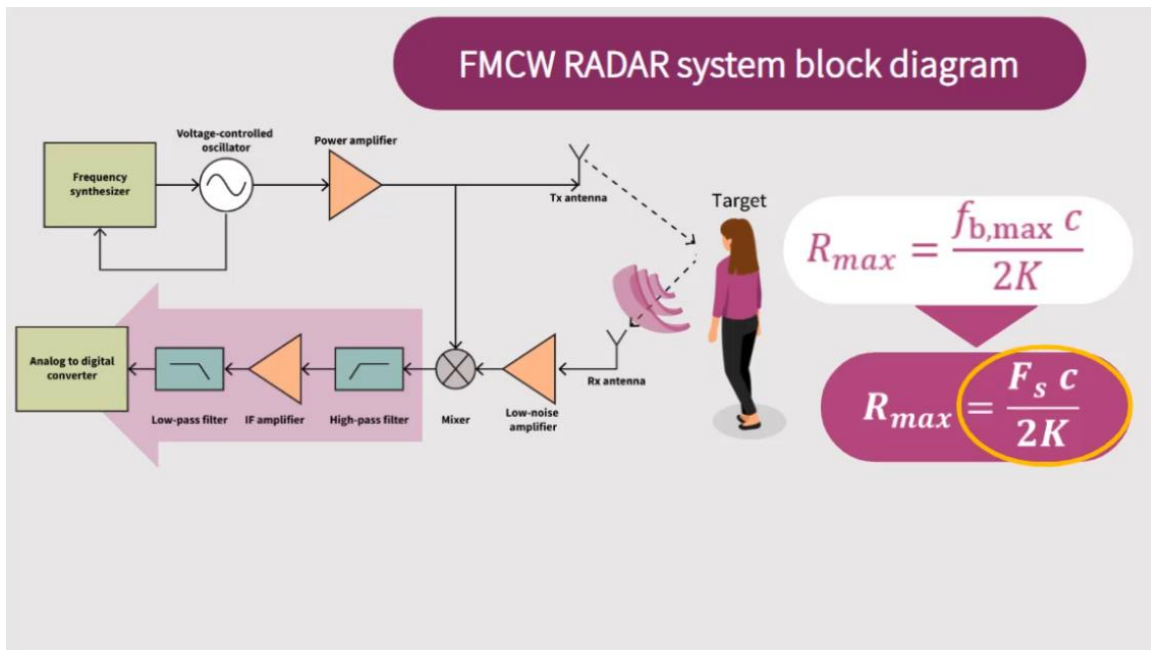
Let's first explore the maximum range.



As shown in the video RADAR basics, the RADAR transmits a chirp signal, a signal that increases and decreases linearly in frequency over time.

Each chirp signal has a defined duration, bandwidth, and resulting slope.

The received signal is reflected from the target object at a range, r , which corresponds to the delay, τ .



The output of the mixer multiplies with the conjugate of the transmit signal.

After substituting x with the transmit and receive signal equations, we get the following mixer output equation of the so-called intermediate frequency signal, in short, IF signal.

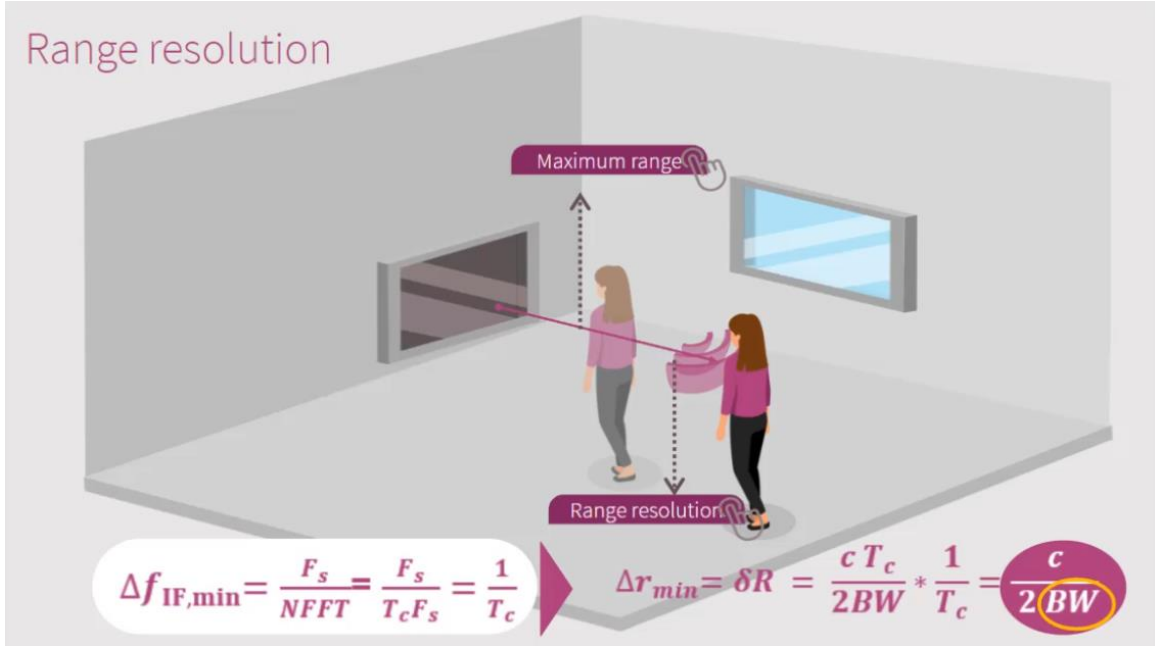
Here, you can see that the output of the mixer, $y-t$, is proportional to the intermediate frequency, also called beat frequency, in short f_b , as f_b is a product of the slope and time delay of the target.

Therefore, by taking the frequency response of $y-t$ using techniques such as FFT, and knowing the frequency index of the peak signal, since τ is proportional to r , we can determine the range, r , to an object.

The maximum unambiguous range, R_{max} , is finally defined by the maximum beat frequency that the receiver system can measure.

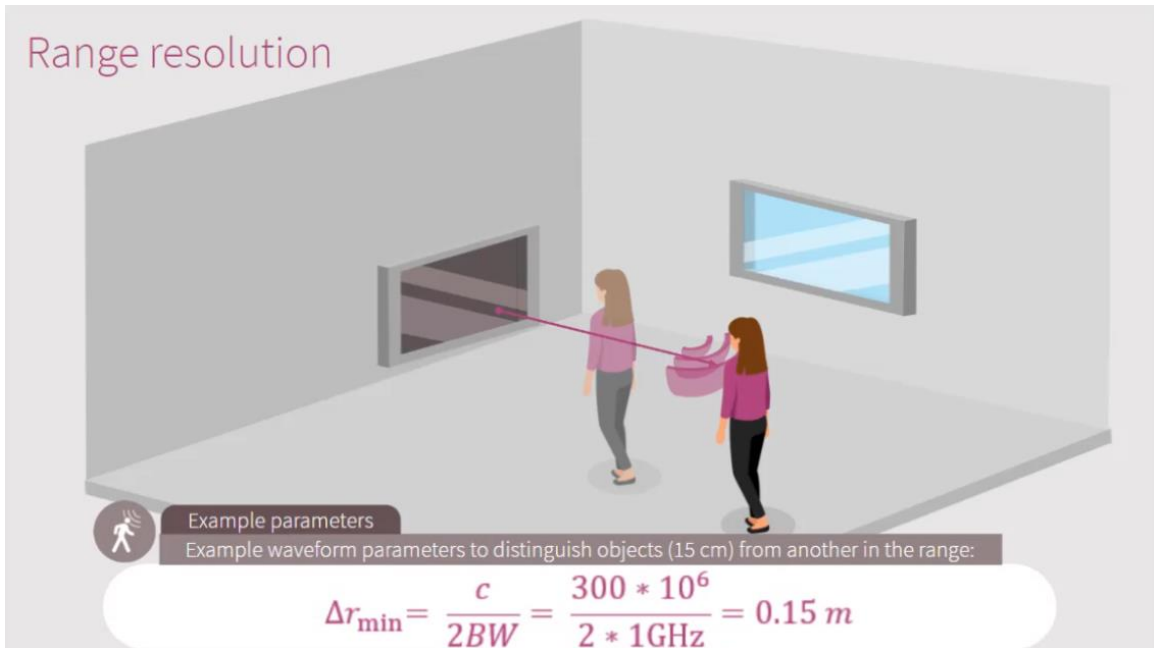
Since the IF signal passes further, namely through the high pass filter, IF amplifier, low pass filter, and the analog to digital converter (ADC), the maximum beat frequency is actually limited by the low pass filter cut-off frequency and the ADC sampling rate, F_s .

Note that this given maximum range corresponds to both, positive and negative frequencies of the FFT.



To come back to our presence detection example, find here example parameters that allow the RADAR chip to detect an object at a distance of up to 5 meters using a range estimation technique based on FFT.

And what about the range resolution?



We can derive the range resolution formula based on the range equation we already derived.

Based on the formula, the distance between two targets is proportional to the minimum IF frequencies (Δf_{\min}) that can be resolved by the sensor.

The minimum frequency resolution is set by the spectral resolution of the RADAR range frequency estimation algorithm such as FFT.

Based on the FFT formula, the spectral resolution is defined as follows.

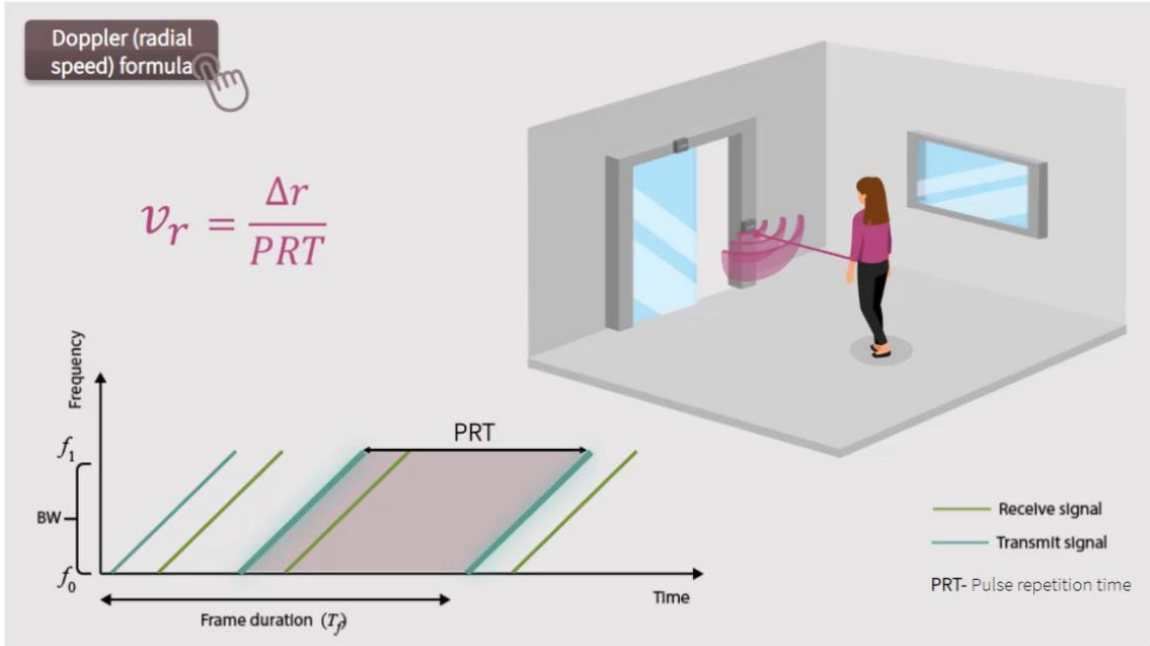
In our case, F_s is the ADC sampling rate.

Assuming NFFT bins are equal to the number of samples per chirp, and substituting the equation, we get the following equation.

You see, the range resolution is only dependent on the bandwidth of the transmitted FMCW signal, which is inversely proportional.

This means that the bigger the bandwidth, the more frequencies are covered, the smaller the frequency intervals are and the better the resolution!

Coming back to our example, find here example waveform parameters to distinguish objects that are a minimum of 15 centimeters apart from each other in the range



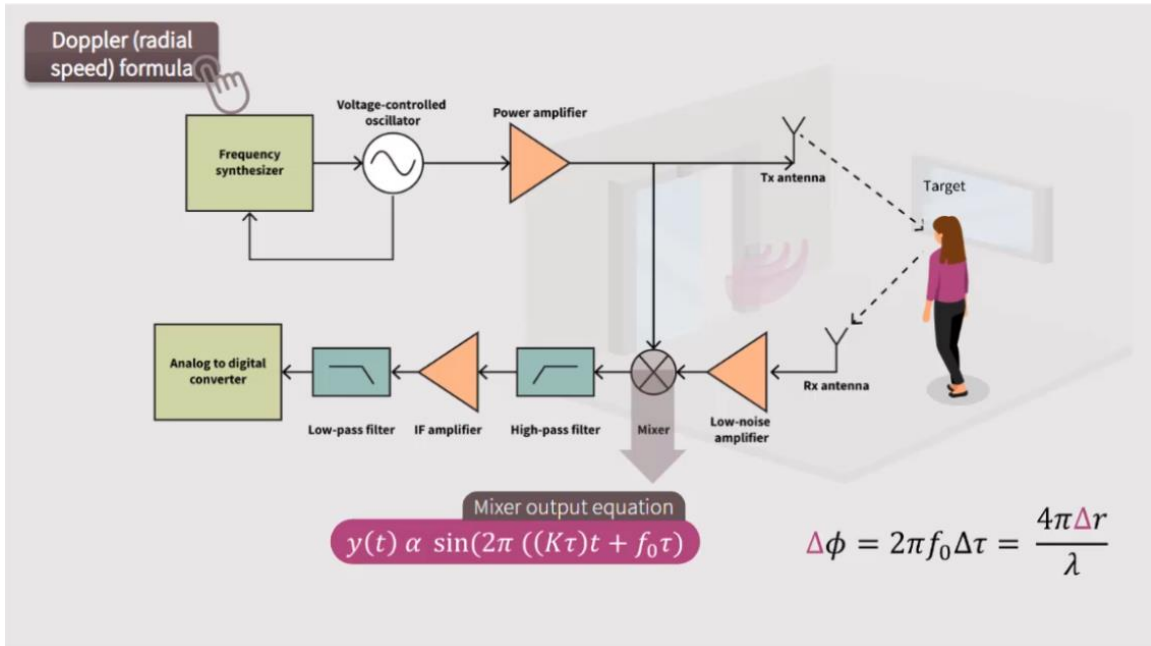
As you can see, the doppler speed is dependent on the pulse repetition time.

But what is behind this formula?

Let's define v_r as the radial speed of the object.

As we already saw, for the FMCW design, PRT is defined as the pulse repetition time, the time duration between two consecutive transmit chirps, and the doppler speed estimation is based on the PRT.

In addition, v_r is the distance traveled by the target (Δr) within the time duration between two consecutive transmit chirps.



Do you remember from the range equation deduction that the phase of the IF signal $y(t)$ is proportional to the range r of the target?

By measuring the phase difference between two consecutive chirps, we can measure the distance traveled (Δr).

Δr is the range difference of the target as it moves within PRT.

Doppler (radial speed) formula

Example parameters

- > Speed of light (c) = $3e8$ m/s
- > Wavelength (λ) = 5 mm
- > Chirp duration (T_c) = 37 μ s
- > Shape_end_delay = 500 μ s
(delay after transmitting chirp signal when there is no transmission)
- > PRT = $T_c + \text{Shape_end_delay}$ = 537 μ s
- > $V_{\text{max}} = 2.3$ m/s

To be precise, substituting derived Δr in the v_r equation, we get the following one.

Therefore, by measuring the phase difference between consecutive chirps, we can determine the doppler speed, v_r , of an object.

The maximum unambiguous doppler speed in this case is then limited by the measurable phase difference that lies in the range of $-\pi$ to π .

For more than one object or target, the respective phase difference contains components from both targets.

In such a case, the phase difference from each target is separated and estimated by applying FFT on the consecutive chirps from the same range bin.

Find here example waveform parameters to get a speed detection of a walking person whose general walking speed is in the range of less than 2.3 meters per second.

Doppler (radial speed) formula

Example parameters

e.g. heart rate: 75 beats per minute equivalent to (75/60 = 1.25 Hz)

- > PRT = 3 m/s
- > Number of chirps (N) = 512
- > $V_{res} = 0.0016$ m/s [v_{res} ...radial speed]
- > $fd_{res} = \frac{2V_{res}}{\lambda} = 0.63$ Hz [fdres ... Doppler resolution]

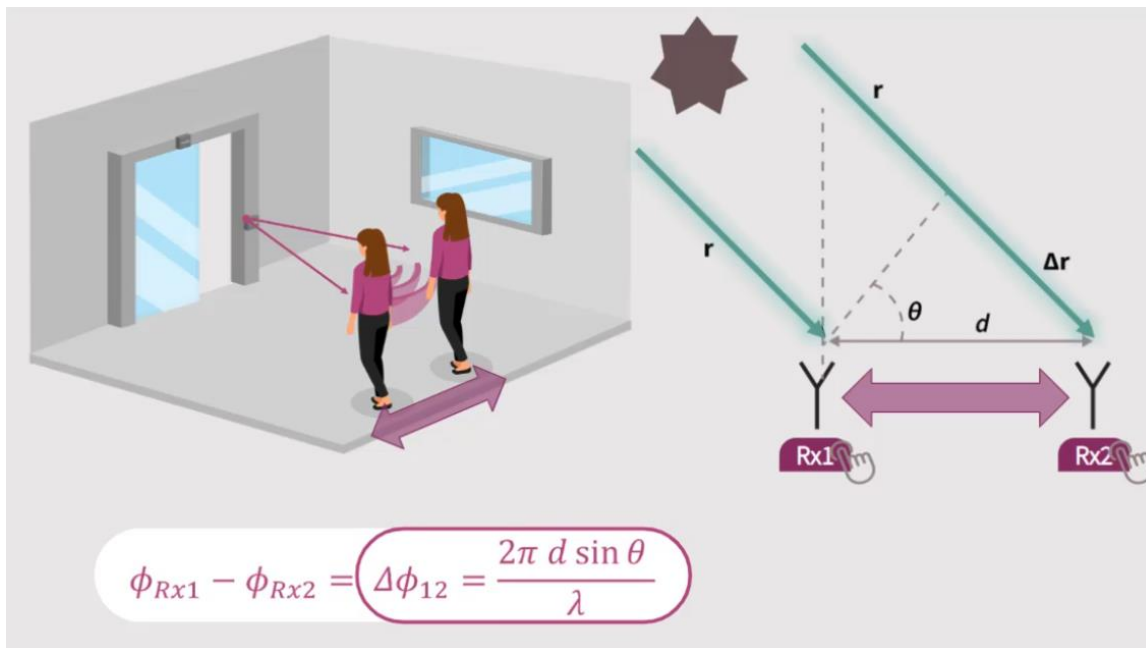
$$v_r = \frac{\Delta\phi \lambda}{4\pi PRT}$$

$$v_{res} > \frac{\lambda}{2N PRT}$$

Similar to the range resolution, the doppler resolution is limited by the spectral resolution of the doppler FFT, which is 2π divided by N.

Substituting results in the v_{res} formula, we get the following equation.

Find here example waveform parameters for capturing the heart rate of a person within two doppler speed data.



Let's stick with our example of presence detection. What if we want to know the angle of the object with respect to the sensor?

Remember that, if we have more than one receiver, we can then estimate the angle of the targets by processing the data across multiple receiver channels – given there is enough SNR.

After range and doppler processing, the remaining phase of the received signal at the output of R-D map from a single target at distance r and angle theta is given as follows, assuming zero phase noise.

Note that here delta phi 1-2 is the phase difference between receiver 1 and receiver 2.

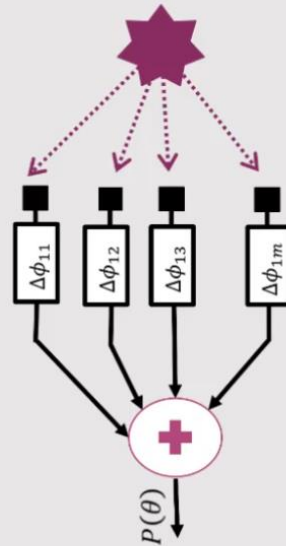
$$\phi_{Rx1} - \phi_{Rx2} = \Delta\phi_{12} = \frac{2\pi d \sin \theta}{\lambda}$$

$$\Delta\phi_{1m} = \frac{2\pi (m-1)d \sin \theta}{\lambda}$$

$$P(\theta) = \sum_{m=1}^M z_m e^{-j\Delta\phi_{1m}}$$

Delay and sum beamforming

$$P(\theta) = \sum_{m=1}^M z_m e^{\frac{-j2\pi(m-1)d \sin \theta}{\lambda}}$$



We can extend and generalize the phase difference to multiple receivers “m” that are uniformly spaced at a distance “d” as follows.

To determine the angle of the target (theta) and the corresponding reflectivity or power P(theta), we multiply the received signal at each receiver z-m with the corresponding phase difference from the reference antenna and coherently sum all the values.

This technique is also known as delay and sum beamforming technique. This equation can also be implemented by taking FFT across the channels.

Maximum unambiguous field of view (Max. angle)

$$\theta < \sin^{-1}\left(\frac{\lambda}{2d}\right)$$

$$\Delta\phi_{12} = \frac{2\pi d \sin \theta}{\lambda} \quad \Delta\phi_{12} \in [-\pi \pi]$$

$$\Delta\theta > \frac{\lambda}{Md \cos \theta}$$

Angle resolution

FFT frequency resolution depends on $\frac{2\pi}{M}$

$$\frac{2\pi d (\sin(\theta + \Delta\theta) - \sin \theta)}{\lambda} \sim \frac{2\pi d}{\lambda} \cos \theta \Delta\theta > \frac{2\pi}{M}$$

The maximum unambiguous field of view is, similar to the derivations for range and doppler, dependent on the phase range of minus pi pi .

The angle resolution is the minimum separation in angle dimension that the sensor can resolve – and this depends on the angle of arrival, in short (AOA), FFT frequency resolution.

Classical AOA techniques such as the one shown at the top are limited by this intrinsic resolution limitation of the frequency estimation technique.

The capon-based AOA technique or minimum variance method improves the resolution based on SNR, interference, and number of snapshots or acquisitions. Find here a reference to this technique.

θ_{max} example:
Parameters to get detections from maximum field of view of 90°

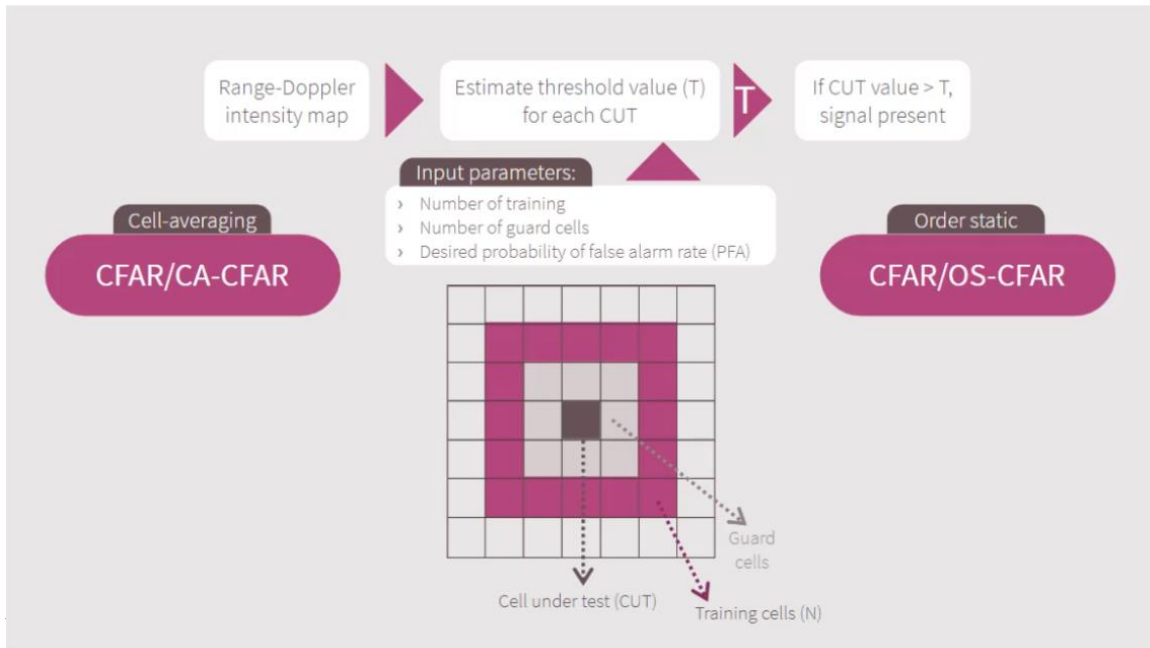
- › Antenna spacing (d) = $\frac{\lambda}{2}$
- › $\theta_{max} = +/ -90^\circ$
- › Note that this value corresponds to field of view after Digital Beamforming (DBF). In addition to this, there should be enough signal strength to perform DBF that is dependent on individual antenna element gain at a given angle (θ)

θ_{res} example:
Parameters to separate detections that are spaced 15° apart at boresight ($\theta = 0^\circ$)

- › Antenna spacing (d) = $\frac{\lambda}{2}$
- › Number of receivers (M) = 8
- › $\theta_{res} \sim 0.25 \text{ rad} \sim 14.3^\circ$

Reference: Van Trees, H. Optimum Array Processing. New York: Wiley-Interscience, 2002

Returning to our example, find here example parameters to get detections from the maximum field of view and angle resolution.



Constant false alarm rate, in short CFAR, is an adaptive threshold-based signal detection technique in the presence of noise.

There are multiple types of CFAR:

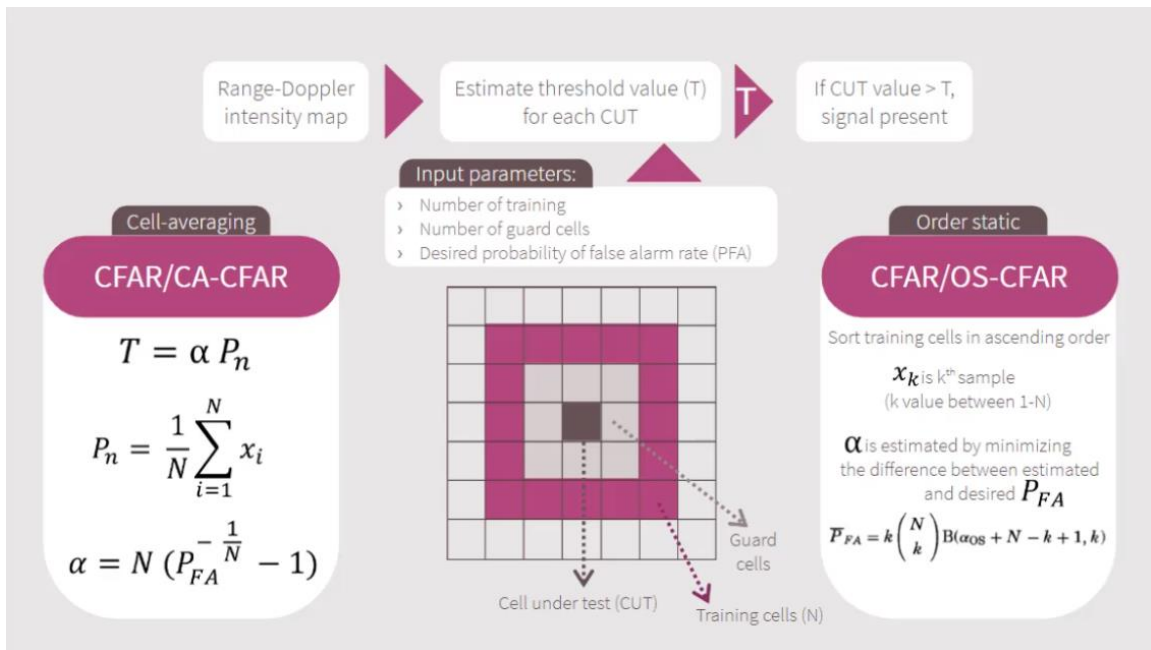
- > Cell-averaging CFAR or CACFAR and
- > Order static CFAR or OSCFAR

The C-FAR technique can be applied on range-doppler FFT maps or range-angle 2D matrices to detect targets with enough signal strength and to remove noise.

The technique can also be extended to 2D or 3D input dimensional data.

Basically, we estimate the threshold value for each cell under test to determine if the signal is present or absent. This threshold value is dependent on multiple input parameters such as number of training cells, guard cells, and desired probability of false alarm rate (PFA).

The user can define the number of guard cells and training cells surrounding the cell under test as shown in the figure.



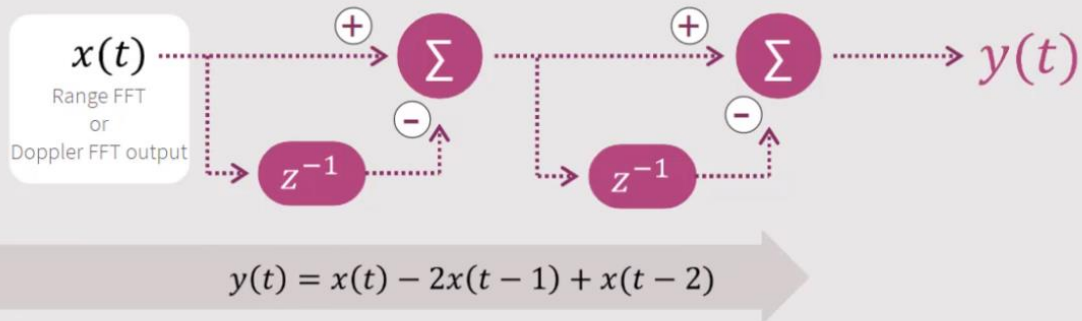
In the cell-averaging technique, the threshold value is proportional to the noise power.

In this CACFAR, the noise is estimated via averaging the values in the “N” training cells X-I, and alpha is given according to this equation.

In contrast, in order static CFAR, instead of averaging the training values, the training cells are sorted, and the kth sample is considered as the noise value.

Moving target indicator (MTI)

First order infinite impulse response (IIR) filter



The moving target indicator filter distinguishes the moving targets from static objects. In example precisely, filters static objects using a first order infinite impulse response filter.

It is a first order infinite impulse response filter.

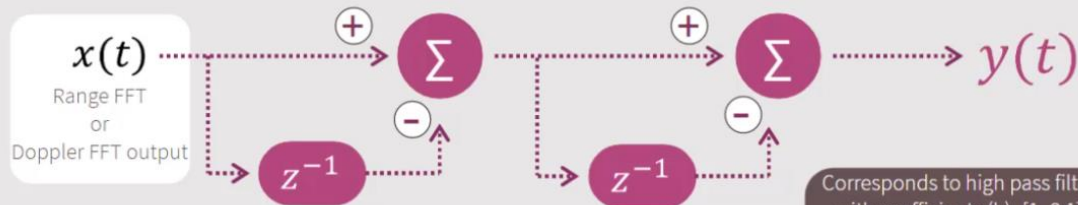
As illustrated in the figure, the filter output $y-t$ is obtained via subtracting or adding the delayed versions of the input signals $x-t$ such as the range or doppler FFT output.

This formulation results in high pass filter coefficients.

Furthermore, this moving target indicator filter h can be generalized to consider more than two previous returns $x-t$ minus and $x-t$ minus 2 via the weighted sum of past returns that are set by user-defined alpha and beta coefficients.

Moving target indicator (MTI)

First order infinite impulse response (IIR) filter



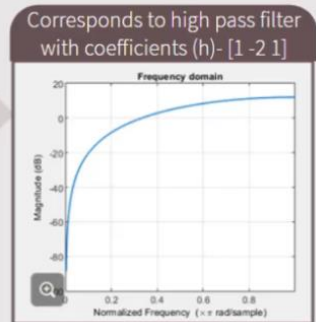
$$y(t) = x(t) - 2x(t - 1) + x(t - 2)$$

$$y(t) = x(t) - h(t - 1)$$

$$h(t) = \alpha x(t) + (1 - \beta)h(t - 1)$$

Generalized form
(weighted sum of the past returns)

$$y(t) = x(t) - \alpha x(t - 1) - \alpha(1 - \beta)x(t - 2) + \dots$$



Here, a Range-Doppler image is obtained after estimating the Range Doppler FFT. The left one is obtained with waveform configurations set to capture the macro-Doppler feature and the right one for micro movement features. In both these cases, we see the Range Doppler image of the target is spread out over multiple bins or multiple points. But they belong to one target.

DBSCAN
Density-based spatial clustering of applications with noise

Requires 2 input parameters:

ϵ *MinPts*

Robust to outliers

Algorithm flow:

- 1
- 2
- 3
- 4

As the name suggests, the density-based spatial clustering of applications with noise, in short, DBSCAN, is a density-based approach to group together points requiring two input parameters:

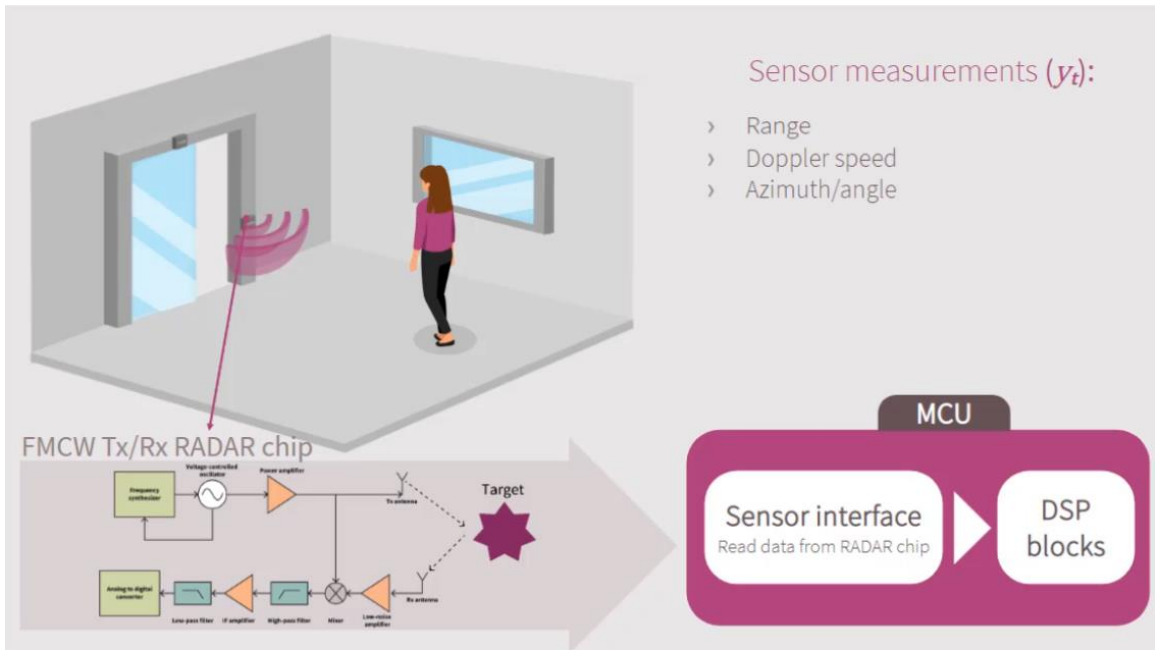
- > Epsilon: the largest radius of neighborhood around a point
- > And minimum points: the minimum number of points in an epsilon neighborhood of that point

The algorithm flows as follows:

1. Find the points in the epsilon neighborhood of every point
2. Identify the core points with more than the minimum number of points of neighbors
3. Find the connected components of core points on the neighbor graph, ignoring all non-core points
4. And finally, assign each non-core point to a nearby cluster if the cluster is epsilon-neighbor; otherwise, assign it to noise

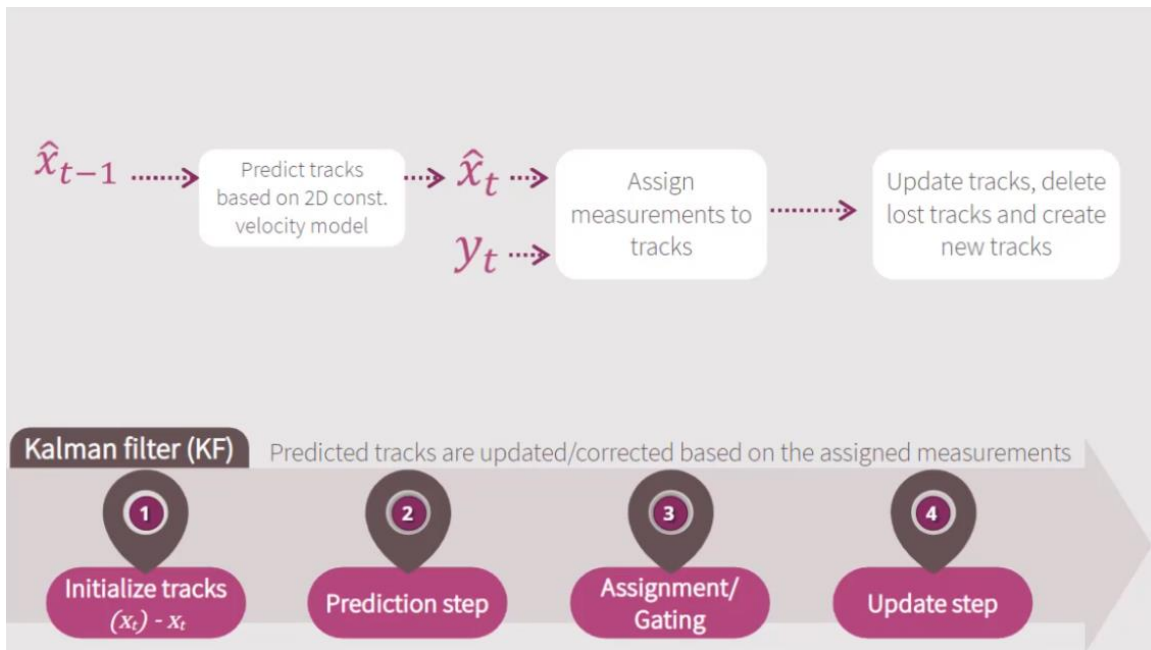
This approach is robust to outliers, and no prior assumption related to the number of clusters or number of objects is required.

An example of detection and clustering of an object in the presence of outliers is shown here.



Not only clustering algorithms are needed, but also tracking algorithms.

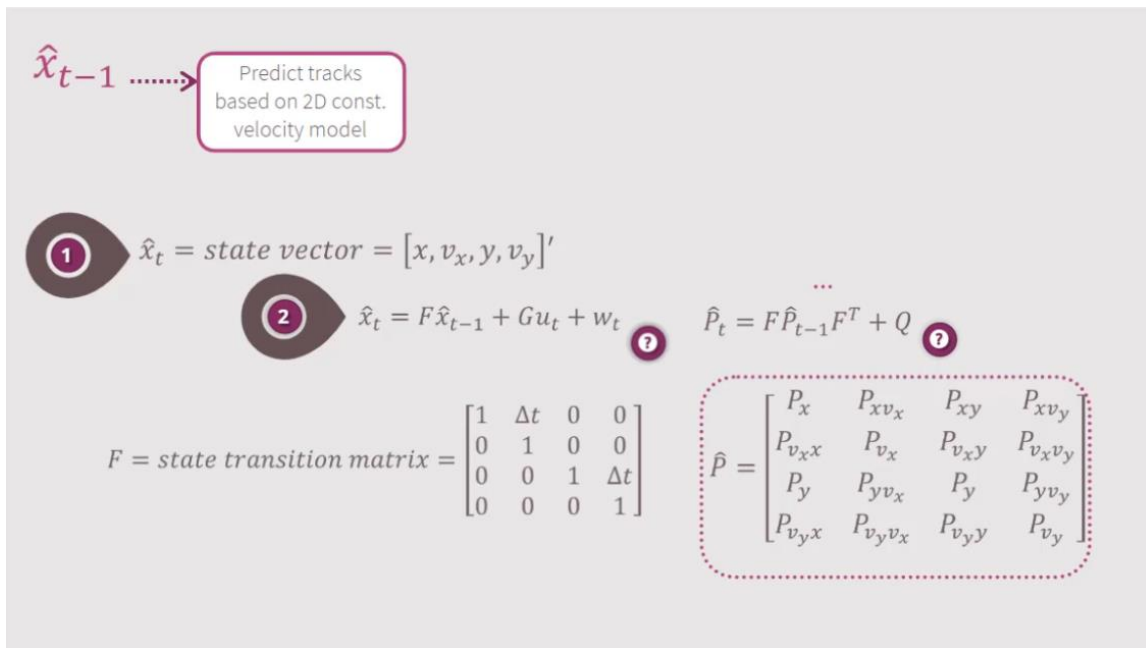
RADAR tracking algorithms predict and track the position and doppler speed of the moving objects over time, based on the incoming sensor measurements.



Sensor measurements (y_t) include estimates from the previously defined algorithm blocks such as range, doppler speed, and angle from consecutive RADAR frames.

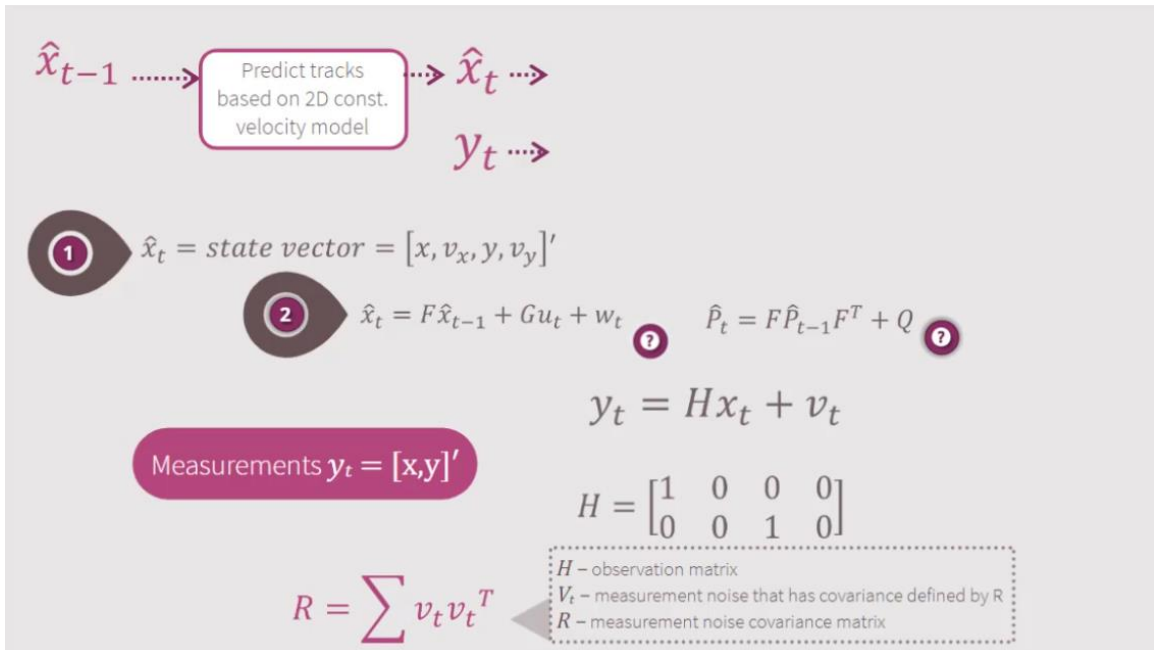
The Kalman filter, in short K-F, is one of the basic tracking algorithms. Its main steps include:

1. Initialize tracks, where x_t is also known as a state vector that includes variables of interest such as position in cartesian coordinates x, y , or polar coordinates
2. Prediction step: in this step, kinematic models such as constant speed and constant acceleration models are considered to predict the position at the next step
3. Assignment or gating, meaning that the incoming measurements y_t from the RADAR sensor are assigned to the predicted tracks; examples are Euclidian distance, Mahalobonis distance, and Hungarian assignment
4. And lastly, update step: in this step, predicted tracks are updated or corrected based on the assigned measurements



Let's go through an example of a Kalman filter formulation to track an object in x, y.

1. First, we define a state vector, consisting of parameters of interest, such as position in x, y, and corresponding speeds
2. Then, in the prediction block, there are two steps to consider: predicting \hat{x}_t and \hat{P}_t . Here, \hat{x}_t cap is the state vector, and \hat{P}_t cap is the covariance matrix of the variables defined in the state vector x. We predict the state vector at the next timestamp d-t, based on the constant speed model, where F is state transition matrix. We assume the external control input and matrix to be zero in this example. Similarly, we predict the covariance matrix value at time t, based on the equation given here
3. Afterwards, we define how the measurements obtained from the RADAR sensor are related to the state vector. In our case, after converting the estimated range, we define the measurements as the doppler speed and the angle values obtained in the cartesian coordinate system. Note that the origin is with respect to the RADAR
4. Lastly, V_t is the measurement noise, and R is the corresponding measurement noise covariance matrix that is related to range resolution and angular resolution values

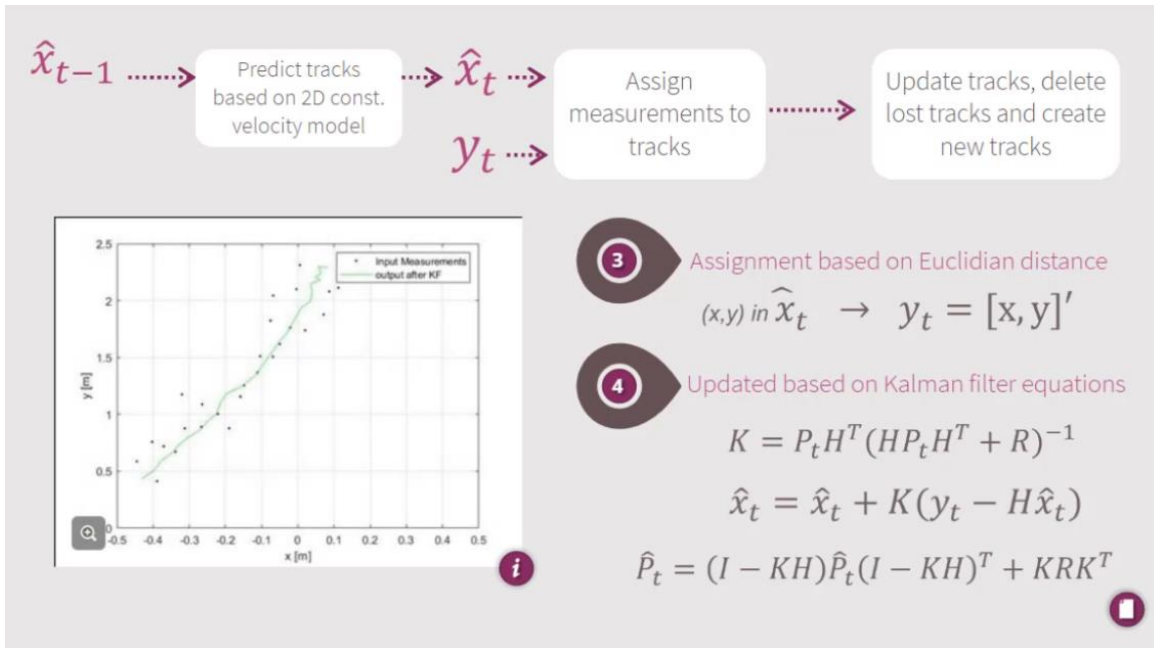


Now it's time to assign the measurements to the predicted tracks.

In this example, the assignment of measurements to the tracks is done based on the Euclidian distance: the distance is calculated using the predicted position values x and y .

The state vectors are then updated based on the Kalman filter update equations: here, K represents the Kalman gain. Derivation of these equations are available.

In this picture, you can see an example track in x - y based on the Kalman filter equations



Note once more that the Kalman Filter is a fundamental tracking algorithm.

Non-linear tracking models such as the extended Kalman filter, in short EKF, and the unscented Kalman filter, in short UKF, can also be implemented on the RADAR data collected from our sensors.



Contacts

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You are now fully familiarized with the FMCW RADAR and understand why it is also beneficial to understand what is happening on the software side of the DSP of FMCW!

If you need further information about this topic, please use the following contacts.

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