Estimating Indoor Walking Velocity Profile Using a Software Radio-based Radar

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***Abstract*—Radar is an attractive technology for long term monitoring of human movement as it operates remotely, can be placed behind walls and is able to monitor a large area depending on its operating parameters. A radar signal reflected off a moving person carries rich information on his or her activity pattern in the form of a set of Doppler frequency components produced by the specific combination of limbs and torso movements. Deploying radars in indoor environments poses however challenges for the interpretation of signals reflected off a moving object due to multipath propagation. Two strategies for the estimation of human walking velocity profile in indoor environments are suggested and discussed. The accuracy of the strategies are evaluated and compared in a field experiment using a flexible and low-cost software defined radar platform. The results obtained indicate that both methods are able to estimate the velocity profile of the person's translational movement with less than 10% error.**

***Index Terms*—Human movement, Velocity profile, Radar, GNU Radio**

I. Introduction

Automatic classification of human activity is an enabler of relevant applications in the healthcare and wellness domains given the strong empirical relation between a person's health and his or her activity profile. As a rule of thumb, the ability of a person to engage independently in strenuous and complex activities entails better fitness and health status, the reverse relation being also generally true. This implication has inspired the design of activity monitoring systems that range from fitness training [1] to early discharge support of postoperative patients [2]. Activity classification may also be used to identify unusual movements, such as falling in elderly care applications.

Different on-body and off-body sensors have been used for activity monitoring as for instance accelerometers [3] and cameras [4]. However, human movement monitoring in health and wellness applications may span for long periods of time and user compliance is very sensitive to the burden level imposed by the underlying sensor technology. Radar is an attractive technology for long term monitoring of human movement because it is an off-body sensor, can be placed behind walls and is able to cover a large area depending on its operating parameters. Furthermore, the coarseness of the information provided by radars is less prone to raise privacy concerns when compared to cameras.

A radar signal reflected off a moving person carries information on his or her activity in the form of a set of Doppler frequency components produced by the specific combination of limbs and torso movements. The Doppler frequency pattern that results from such a complex movement sequence is called ”Micro-Doppler Signature”. If for a given activity, these Doppler components can be categorized into unambiguous profiles or “footprints”, then radar signals may be used to identify specific activities over time. Although not each and every human activity results in a distinguishable signature, the accurate extraction of unique features may be sufficient to enable classification.

A major feature for the classification of human activities using Doppler signature is velocity profile, *i.e.*, the velocity of different parts of the body over time [5]. Moreover, the velocity profile of a walking person shows different states (accelerate, decelerate, sudden stop, change in direction, etc.) that are useful to be identified in various applications. In general, a careful observation of how a person's gait and velocity profile develops over time provides insights that can be used for timely intervention (if and when needed) in health and elderly care applications.

Deploying radars in health and wellness applications at the user's home will be facilitated if such systems are low cost, easy to deploy and safe. Low radiation emission ensures safety for the user while multiple room coverage per radar unit eases deployment at home. However, extracting useful information from radars deployed in an indoor environment, where subjects may spend most or all their time, poses a challenge due to multipath propagation. The unfavorable environment makes it more difficult to identify Doppler components that carry information on the actual translational motion of the person.

This paper suggests and compares two strategies for estimating a person's walking velocity profile in indoor environments. The main contributions to the area of unobtrusive monitoring in health and wellness applications are as follows:

- Two methods to estimate the velocity profile of human translational motion from the Doppler signature obtained in a form of time-frequency spectrogram are proposed and evaluated.
- An experimental radar platform based on low-cost software-defined radio hardware and open source software is implemented and its use for indoor monitoring

of human movement is validated. The platform offers the opportunity of realizing field experiments at an expedited pace and low budget.

The remainder of this paper is organized as follows: Section II reviews related work in the area of human activity monitoring and characterization; Section III describes a human movement model for assisting in the identification of the major Doppler components in the radar signal; Section IV introduces basic radar concepts like radar cross section and the radar signal model; Section V discusses spectral estimation and proposes two methods for estimating a person's walking velocity profile from the received radar signal; Section VI describes the software defined radar platform and the experimental setup used in the validation experiments. The estimation results are presented and evaluated in Section VII. Finally, Section VIII summarizes and concludes the paper based on the results obtained.

II. Related Work

The data required for human movement analysis in indoor environments can be gathered through on-body or off-body sensors. In the former category, triaxial accelerometers have been widely investigated for quantifying and classifying human activities [3]. The main disadvantage of on-body sensors is that these must be carried by the monitored subject at all times, a true inconvenience when monitoring periods span for weeks or months. In elderly care applications, where long monitoring periods are expected, subjects can also be forgetful or uncooperative thus hampering the data collection process.

Off-body sensing for movement analysis can be performed using technologies such as cameras [4], ultrasound [6] or pyroelectric infrared (PIR) sensors [7]. These approaches suffer however from limited range indoors as line of sight is usually constrained to a single room. The range limitation of these technologies means that many sensors are required to cover a single building. Furthermore, these multiple sensing units must be networked for data collection thus increasing the deployment and maintenance complexity of the system. Radars on the other hand are able to monitor large areas. Depending on the transmission parameters, radars can also be used for through-the-wall sensing [8].

The use of radars for human activity monitoring and classification has also been intensively investigated. Anderson [9] used multiple frequency continuous wave radar for classification of humans, animals and vehicles. Otero used a 10GHz CW radar using micro-path antennas to collect data and to attempt classification [10]. Gurbuz *et al.* proposed a simulation based gender discrimination using spectrograms of radar signals [11]. Hornsteiner *et al.* applied radars to identify human motion [12]. Kim *et al.* used artificial neural network for classifying human activities based on micro-Doppler signatures [5]. All these papers used Fast Fourier Transform based frequency estimation. There is also previous work on using other transforms. Geisheimer *et al.* [13] introduced the chirplet transform as a spectral analysis tool. The Hilbert-Haung Transform for non-linear and non-stationary signals in wide band noise radars is also suggested by Lay *et al.* [14]. A complex but more accurate iterative way to obtain each pixel in the spectrogram in a bid to improve the frequency resolution and suppress the side lobes of the fast Fourier transform is also suggested by Du *et al.* [15].

Even though the above authors have treated different aspects in human activity monitoring in general, the estimation of velocity profile in indoor environment where the received signal is plagued with multipath propagation was not specifically treated. In this paper, we suggest methods to characterize a person's walking velocity profile from a spectrogram estimate. Moreover, we used high resolution parametric spectral estimator (MUSIC) and compared its performance with the commonly used Fast Fourier Transform.

III. Human Movement Model

Our starting point for human activity characterization is the definition of a movement model. After studying the relationship between the different parts of the body during locomotion, features that have unique values in different activities can be identified. In this regard, the person's velocity profile is one of the important features that can be used to achieve activity classification.

The velocity profile refers to the instantaneous temporal displacement that the different parts of the human body attain during movement. Most of the human movement models available rely on dividing the non-rigid human body into the most significant rigid parts and modeling the velocity profile of these components. One of the most used models [16] decomposes the body into 12 parts consisting of the torso, lower and upper part of each leg, lower and upper part of each arm, the head and each of the right and left foot. This model also describes the kinematics of each of these body parts as a person walks with a particular velocity. Another known model was based on 3-D position analysis of reflective markers worn on the body using high resolution camera [17]. This model states that the velocity profile of each body part can be represented using low-order Fourier series. Using this model as a basis, we have described a modified human movement velocity profile as follows.

Assume a person is moving at a constant velocity V in a certain direction and that the human body consists of M rigid parts. The velocity profile of each body part, $V_m(t)$ can be represented as a sum of sinusoids given by:

$$\begin{aligned} V_m(t) \quad = \quad & V + A \cdot \{k_{m1} sin(\omega_c t + p_m) \\ & + k_{m2} cos(\omega_c t + p_m) \\ & + k_{m3} sin(2\omega_c t + p_m) + k_{m4} cos(2\omega_c t + p_m)\} \end{aligned} \tag{1}$$

Note that the velocity profile of each body part V_m is characterized by the amplitude constants $k_{m1}, ..., k_{m4}$ and a phase constant $p_m (0 \leq p_m \leq \pi)$. The oscillation amplitudes $k_{m1}, ..., k_{m4}$ are largest for the legs and smallest for the torso. The phase p_m reflects the locomotion mechanism of the body. For example, the right leg and left arm combination move 180^o

out of phase with respect to the left leg and right arm. A is a constant that has a specific value for different human activities. The frequency of oscillation of the body ω_c, is called cadence frequency and can be related to the velocity of the person by $\omega_c = 2\pi B \cdot \sqrt{V}$, where B is a constant that depends of the type of human activity.

A simulation of the velocity profile of a walking person based on the model stated above is shown in Figure 1. As the figure shows, the amplitude of oscillation of each body part is different; however, all body parts oscillate at the same frequency ω_c and its second harmonics $2\omega_c$.

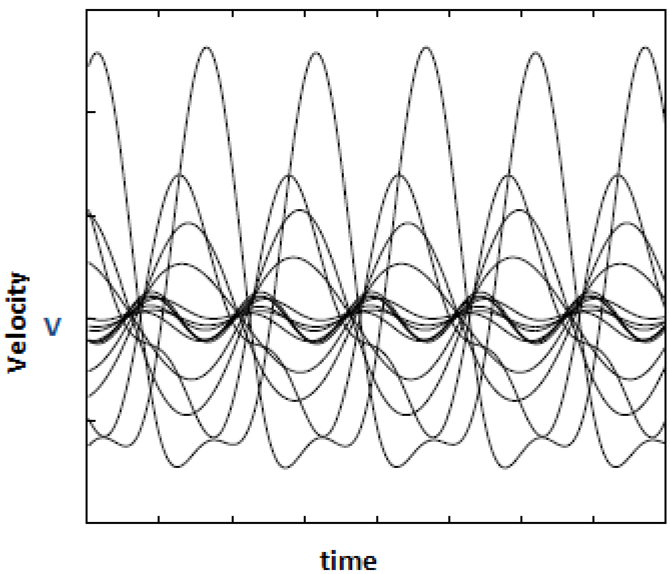

Figure 1. Human movement velocity profile [12]

The translational velocity of the body is normally time-varying. Therefore, the oscillations of the body parts in (1) will be superimposed on the time varying velocity profile of the body. The torso has the smallest oscillation amplitudes $k_{m1}, ..., k_{m4}$ and therefore the translational velocity V of the body can be approximated by the velocity of the torso. The velocity profile of the other body parts can be expressed as sinusoids superimposed on the velocity profile of the torso. Equation (1) can thus be modified to:

$$\begin{aligned} V_m(t) \quad = \quad & V_{torso}(t) + A \cdot \{k_{m1} \sin(\omega_c t + p_m) \\ & + k_{m2} \cos(\omega_c t + p_m) \\ & + k_{m3} \sin(2\omega_c t + p_m) + k_{m4} \cos(2\omega_c t + p_m)\} \end{aligned} \quad (2)$$

IV. Radar in human sensing

Radar is a device that transmits electromagnetic waves, receives the signal reflected back off the target and extracts information about the characteristics (range, velocity, shape, reflectivity, etc.) of the target. The amount of electromagnetic energy that a target is capable of reflecting back is measured in terms of the radar cross section of the target. Doppler radars are those that measure the velocity of a target based on the Doppler effect, *i.e.*, an electromagnetic wave hitting a moving target undergoes a frequency shift proportional to the velocity of the target. The radar cross section and velocity profile are constant and easy to determine for a rigid body moving at a constant speed. However, as discussed in Section III, the human body locomotion is quite complicated. The radar cross section and the signal model for radar based human movement monitoring are discussed in the following sections.

A. Human body Radar Cross Section

Radar cross section (RCS) is a measure of signal reflectivity of an object and is usually expressed in a unit of area (*e.g.* m^2). RCS depends on the frequency of the transmitted signal and parameters of the target such as size, shape and material [18]. The RCS of a moving person is challenging to model because it is composed of multiple semi-independent moving parts. A simple additive approach to create an RCS model by adding up the contribution of each body part is commonly adopted. The contribution of each part can be assumed to remain constant during motion without significant error. In addition, the total RCS can be assumed to be half of the body surface area which is exposed when the person is facing the radar; this area is typically listed as $1m^2$ [19]. Each of the 12 major parts of the human body listed in Section III contribute a fraction of the RCS. The torso has the highest RCS fraction followed by the legs and arms. The head and feet have the least contribution. Particularly, the percentage contribution of each body part is listed as: torso 31%, arms 10% each, legs 16.5% each, head 9% and feet 7% [19].

As the torso has the highest RCS of all the moving body parts, the velocity profile of the torso can be estimated by picking out the strongest component from the received Doppler signal.

B. Signal Model

Doppler radars measure the frequency shift of electromagnetic waves due to motion. The Doppler frequency shift of an object is directly proportional to the velocity of the object and the carrier frequency of the transmitted signal as described next.

Assume a narrowband, unmodulated signal $ae^{j(2\pi ft+\phi_o)}$ is transmitted where a, f and ϕ_o are the amplitude, carrier frequency and initial phase respectively. The signal received at the receiver antenna being reflected off a person has a time varying amplitude $a(t)$ and a time varying phase change $\phi(t)$ given by $a(t)e^{j(\omega t+\phi_o+\phi(t))}$. Hence, the received baseband signal after demodulation is reduced to:

$$y(t) = a(t)e^{j(\phi(t))} \quad (3)$$

The Doppler frequency shift f_d is the rate of change of the phase of the signal, *i.e.*, $f_d(t) = -\frac{1}{2\pi} \cdot \frac{d\phi(t)}{dt}$. This shows that the Doppler shift of a rigid target moving at a velocity $V(t)$ is given by $f_d(t) = 2\frac{V(t)}{\lambda}$ in a monostatic (radar transmitter and receiver co-located) scenario where λ is the wavelength of the transmitted radio wave. It is stated in Section III that the different rigid parts of the body have their own time-varying velocity profile superimposed on the body velocity. Therefore, each of these body parts have their own time-varying Doppler shift, *i.e.*, $f_{d_m}(t) = 2\frac{V_m(t)}{\lambda}$ where $V_m(t)$ is the velocity profile of each body part. It is however generally challenging to extract the velocity profiles of each body part for the following reasons:

- The received signal is a superposition of signals that consist of Doppler shifts of different moving parts. Moreover, each body part has different RCS resulting in different contribution to the aggregate signal.
- There is significant multipath fading in indoor environment which results in further additive components to the resulting signal.
- A radar measures only the radial component of the velocity of the person, and thus only a portion of the movement can be estimated with signals from a single radar.

The content that follows emphasizes on how to estimate the velocity profile of the body from the aggregate received signal.

A typical walking of a person in an indoor environment is described by non-uniform motion, *i.e.*, the velocity profile of the body varies with time. However, physical constraints limit the person from changing velocity during short time intervals. Consequently, the person's velocity can be assumed to remain constant during short time intervals. In other words, a non-uniform human motion can be viewed as a uniform motion over small time or displacement intervals. This means that, even though the received signal is non-stationary, it can be assumed as a piece-wise stationary signal. Based on this argument, the received signal during a small piece-wise stationary interval can be assumed to be a summation of a certain number of sinusoids. If D sinusoids are assumed, the received signal after sampling can be given by:

$$y\left[n\right] \quad = \quad \sum_{d=1}^{D}\left[a_d \cdot e^{j\left(\frac{4\pi V_d}{\lambda}n+\phi_d\right)}\right] \tag{4}$$

where $y\left[n\right]$ is a sample at time instant nT ($1/T$ is the sampling frequency) and a_d, V_d and ϕ_d are respectively the amplitude (proportional to the RCS), velocity and initial phase of each Doppler frequency component. The indoor environment consists of stationary objects such as walls that have larger RCS than the human body. The signal reflected from these stationary objects has zero Doppler frequency shift. Moreover, there is a strong direct signal between the transmitter and receiver antennas of the radar. The resulting effect is a strong DC component in the baseband radar signal. The received signal can then be expressed as:

$$y[n] = a \cdot e^{j\phi} + \sum_{d=1}^{D}\left[a_d \cdot e^{j\left(\frac{4\pi V_d}{\lambda}n+\phi_d\right)}\right] \tag{5}$$

The number of sinusoids D may change between consecutive intervals, but it is assumed to remain constant to avoid complexity. The value of D can be taken as small as the number of body parts described in Section III; however, but it is generally better to assign it a larger number to obtain a smooth Doppler spectrum pattern.

V. VELOCITY PROFILE ESTIMATION

The received radar signal consists of many frequency components as described in the previous section. If piecewise stationarity is assumed, a joint time-frequency estimation can be used to decompose the received signal into these components. In order to estimate the spectral content of a signal, non-parametric or parametric spectral estimators can be applied [20]. In this work, the short time Fourier transform (STFT) and a high resolution parametric estimator, MUltiple SIgnal Classification (MUSIC) are used.

Once the spectral components of the signal are obtained, the next step is to estimate the velocity profile of the person's torso. This can be accomplished in different ways using the joint time-frequency estimation. In this paper, two methods are suggested and their performance are compared: maximum power and weighted power methods.

A. DC removal

As shown in (5), there is a strong DC component in the aggregate received signal. This component contains no information and makes the spectral magnitudes of the other relevant frequencies almost invisible in the spectrogram.

There are different techniques to eliminate a DC component from a signal. The simplest method available is adopted here, *i.e.*, averaging. The average value of the signal is computed and subtracted from the aggregate signal as follows.

$$\hat{y}[n] = y[n] - \frac{1}{N}\sum_{n=1}^{N} y[n] \tag{6}$$

where N is a large number. The remaining signal $\hat{y}\left[n\right]$ can be assumed to consist of reflections from moving objects only.

B. Spectral estimation

The short time Fourier transform (STFT) applied on the signal, $\hat{y}\left[n\right]$ is given by:

$$Y\left[k, n'\right] = \sum_{n=n'}^{n'+L} \hat{y}\left[n\right] \cdot e^{-j2\pi nk/N} \tag{7}$$

where L is the number of signal samples taken in each consecutive computation (window size); n', which is set to multiples of L, represents the start of the moving window transform; k represents the k^{th} frequency component of the signal and N is the size of the FFT. The window size L is set based on the duration over which the signal is assumed stationary. This form of short time FFT computation is also called sliding window FFT.

For the sake of comparison, a MUSIC [20] based spectral estimation is also applied to the received signal. MUSIC is a parametric spectral estimator based on eigenvalue decomposition. Sliding window MUSIC based spectral estimation is not commonly used; however, it is intuitive that it can be applied similarly to sliding window FFT. The major advantage of parametric spectral estimators like MUSIC is that the spectral resolution is independent of the window size L. In the STFT, the window size is a trade-off between stationarity and spectral resolution. However, the MUSIC method requires a priori knowledge of two parameters: the auto-correlation lag parameter m and the number of sinusoids D [20]. The performance of the MUSIC method can be better or worse than STFT based on the setting of these two parameters.

The joint time-frequency spectral estimation is represented using the spectrogram, a color plot of the magnitude of frequency components as a function of time and frequency. The pixels in the spectrogram represent the power at a particular frequency and time, which is computed as: $P\left[k, n'\right] = \left|Y\left[k, n'\right]\right|^2$.

C. Velocity estimation methods

As discussed in Section III, each body part has its own velocity profile superimposed on the velocity profile of the torso. The instantaneous torso velocity $v_{torso}\left[n'\right]$ is expressed in terms of the torso Doppler frequency as $v_{torso}\left[n'\right] = \frac{2\pi}{\lambda} f_{torso}\left[n'\right]$. The following two methods can be used to estimate the torso Doppler frequency at a particular time n' from the spectrogram.

Maximum power method: As described in Section III, the torso has the largest RCS of all the body parts. Thus, the frequency component which has the highest power must be the Doppler frequency component of the torso since the strongest DC component is already removed. The maximum power method selects the frequency of maximum power from each spectral window in the computed spectrogram, *i.e.*, $f_{torso}\left[n'\right] = f\left[k_{torso}, n'\right]$, where, k_{torso} is the frequency index at which $P\left[k, n'\right]$ is maximum. However, selecting the maximum frequency component returns the torso frequency component only when there is motion. If there is no motion, the received signal $\hat{y}[n]$ in (6) consists of only background noise and therefore selecting the strongest frequency component gives a wrong estimate of the torso frequency (which is zero). A parameter must thus be selected to distinguish motion and no-motion intervals (for instance, in Figure 4, the interval of no-motion is $0 - 3\ s$). This parameter will be computed from the signal received when there is no motion and used as a threshold. The total signal power in the spectrogram column is one of the suitable parameters that can be used to distinguish these intervals. This parameter is computed and averaged over the duration of no-motion to determine a threshold, *i.e.*, $P_{thr} = average\{\sum_{k=1}^{N} P[k, n']\}$. Therefore,

$$f_{torso}\left[n'\right] = \begin{cases} f\left[k_{torso}, n'\right] & if \quad \sum_{k=1}^{N} P[k, n'] > P_{thr} \\ 0 & else \end{cases}$$

Weighted power method: The maximum power method requires a threshold which may fail to distinguish the motion and no-motion intervals correctly. This can result in a non-zero velocity estimate in absence of motion or zero velocity even though there is motion. Thus a method that pulls the velocity to zero when there is no or little motion without using a threshold is desirable. This method should also pull the resulting velocity estimate to the torso velocity when there is motion. One possible way to do this is to estimate $f_{torso}\left[n'\right]$ as a power-weighted average frequency in each spectrogram column n', *i.e.*,

$$f_{torso}\left[n'\right] = \frac{\sum_{k=1}^{N} f\left[k, n'\right] \cdot P\left[k, n'\right]}{\sum_{k=1}^{N} P\left[k, n'\right]}$$

This is based on the assumption that the frequency index range considered in the spectrogram is $[-Fs/2 : Fs/2]$ (Fs is the sampling frequency) or the zero frequency is the central point in the spectrogram.

The major problem of the weighted power method is that it results in a biased estimate when image frequencies are present. Image frequencies are those Doppler frequencies that occur on the opposite side of the actual Doppler frequency pattern in the spectrogram. These occur due to multipath propagation in indoor environments. For instance, when a person is moving towards the radar, the Doppler frequencies are positive. However, there are also signals that reflect on the back of the person and received in the aggregate signal. The person is moving away from the radar with respect to these signal paths resulting in negative (image) frequencies. The presence of image frequencies makes the weighted power estimate biased with respect to the actual torso frequency. However, the rays that reflect off the back of the person travel longer distances as compared to the rays that reflect off the front of the person and therefore, these components have lower power levels. The low power level of image frequencies reduces their impact on the weighted power method.

The maximum power method is not affected by the presence of image frequencies as it simply selects the strongest frequency component. The weighted power method however performs well even in static conditions and is easier to apply as there is no need for a threshold.

VI. GNU Radio-based radar

The torso velocity profile estimation discussed in the previous section was evaluated in a set of experiments using a GNU Radio-based radar. GNU Radio is an open source and free programming toolkit for realizing software defined radios [21]. The toolkit consists of a set of signal processing blocks that can be configured to work with different hardware components. The Universal Software Radio Peripheral (USRP) is a general purpose programmable hardware that is designed to be used as a frontend for GNU Radio [22].

GNU Radio and USRP have been widely used for prototyping research in communication systems [23]. Their adoption in a wide range of applications is motivated by the low cost and relative ease to use. However, the use of USRP as a platform for building active radars is limited due to its low power and limited bandwidth. A possible design of a USRP based long-range pulse radar is discussed in [24]. To the best of our knowledge, our work is the first using USRP and GNU Radio as a short-range (indoor) active radar.

In our experiments, a USRP is used in conjunction with GNU Radio to implement unmodulated continuous wave radar. The USRP was equipped with a XCVR2450 daughterboard which works as the radar RF frontend operating in the $2.4 - 2.5$ and $4.9 - 5.9\,\mathrm{GHz}$ bands. Figure 2 shows the schematics of our radar. The setup uses two separate USRPs, one for transmission and the other dedicated for reception. A cable between the boards ensures the two boards are synchronized to a common clock.

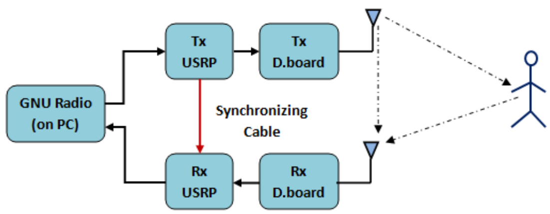

Figure 2. Experimental Setup

This radar platform is both low-cost and very flexible. The carrier frequency, transmit power, receiver gain, and other parameters are easily configurable in software.

VII. Evaluation

In the evaluation experiments, a person's movement in a confined area was measured using radar transmission frequency of $5\,\mathrm{GHz}$ and transmission power of $30\,\mathrm{dBm}$ (including antenna gains). The received signals were recorded in a data file and processed offline using MATLAB. The signal was low-pass filtered and decimated to a sampling rate Fs of $500\,S/s$. A window size of 100 samples ($0.2s$), FFT size (N) of 500 and an overlap of 75% between the sliding windows were used in the computation of both STFT and MUSIC spectrograms. In MUSIC, the autocorrelation lag parameter m is set to $0.5L$ and the number of sinusoids D is set to 25. Such a value of D was chosen after experimenting on the received signal and taking into a account the discussion in Section IV.

Some important parameters of motion that can be easily observed from the spectrogram are discussed and compared with the actual motion of the subject. The velocity profile is estimated using the two methods discussed in Section V-C. These velocity estimation methods are evaluated by computing the total distance covered (from the velocity profiles) and comparing this with the actual distance covered by the subject (measured manually). The weighted mean method is then used to estimate and compare velocity estimations from the STFT and MUSIC based spectrograms.

The following experiment was done in a $2\,m$ wide and $12\,m$ long corridor as shown in Figure 3, to verify the velocity profile estimation discussed in Section V. The person stood at a distance of $12\,m$ in front of the radar for about $3\,sec$ and then started walking towards the radar. A timer shows that it takes the person about $10\,sec$ and 15 steps to complete the $12\,m$ by walking.

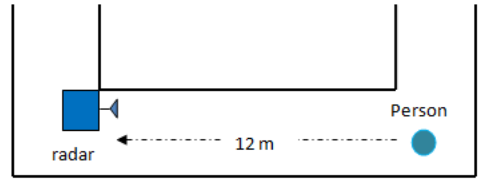

Figure 3. Experiment-4

A. Spectrograms

The STFT and MUSIC based spectrograms obtained from this experiment are shown in Figure 4 and 5, respectively. These spectrograms show the micro-Doppler pattern of the motion of the target over time.

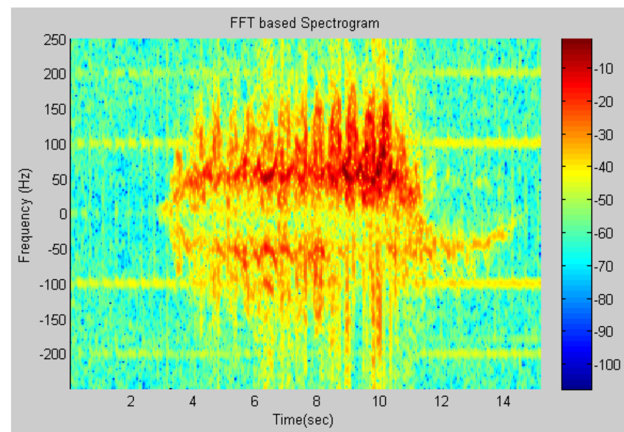

Figure 4. STFT based Spectrogram Estimation

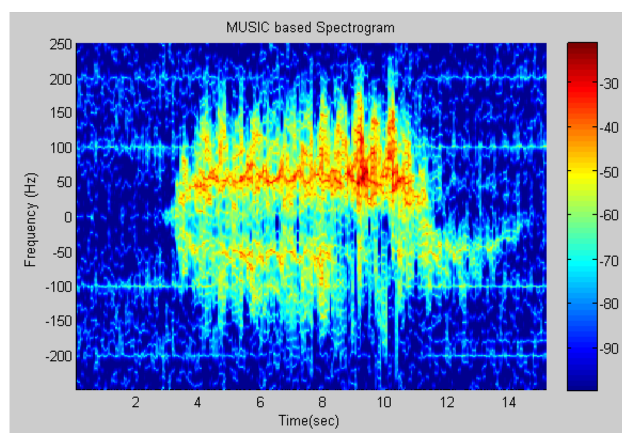

Figure 5. MUSIC based spectrogram estimation

The following observations can be derived from these spectrograms:

- The time duration of motion and the number of steps obtained manually match the spectrogram behavior. The latter, which is counted to be 15 during the experiment, is equal to the number of spikes in the spectrogram (which is also 15 as Figure 4 shows more clearly).

- Even though the person is moving towards the radar (positive Doppler frequency), the spectrograms show that there is an image micro-Doppler pattern of weaker power in the negative Doppler frequencies. This reflects the discussion in Section V-C.
- The STFT spectrogram has lower resolution than the MUSIC spectrogram. The STFT micro-Doppler pattern is smooth as compared to a spiky MUSIC spectrogram that resolves the strongest frequencies as Figure 5 shows. Therefore, it can be deduced that the MUSIC spectrogram helps to observe the specific contribution of each of the rigid parts of the body.

B. Velocity Profile

The torso velocity profile of the experiment estimated from the STFT spectrogram is shown in Figure 6. In order to verify the velocity estimation methods, a part of the motion where the torso velocity is positive is considered (between $3\,sec$ and $11\,sec$ as shown in Figure 4).

The distance the person moved can be estimated as the area under the velocity curve. That is, $Distance = \Delta n' \cdot \sum_{n'=3sec}^{8sec} v_{torso}\,[n']$. A total distance of $13.26\,m$ is obtained from the maximum power method which gives an error percentage of only 10.5% as compared to the actual distance of $12\,m$. Similarly, a total distance of $11.34\,m$ is obtained from the weighted power method which gives an error percentage of only 5.5%. These results show that both torso estimation methods give good results.

The average velocity of the person can be estimated by taking the average value of the torso velocity over the motion interval, *i.e.*, $V_{ave} = average(v_{torso})$. An average velocity of $1.42\,m/sec$ is obtained from the experiment. The acceleration when motion starts (at $3\,sec$) and the deceleration when motion stops (at $11\,sec$) are also evident from the figure.

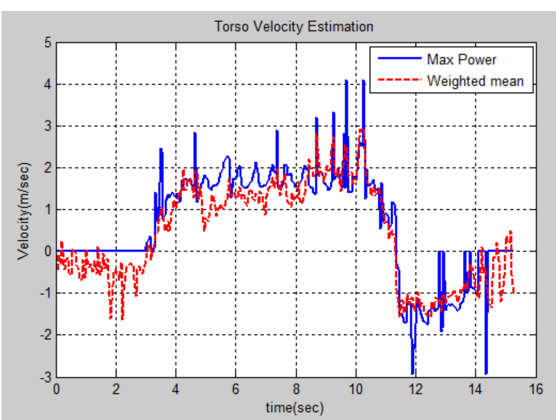

Figure 6. Torso velocity estimations comparison

C. STFT vs MUSIC

The spectrograms in Figure 4 and 5 show that MUSIC is a good spectral estimator to resolve the contribution of the rigid parts of the body to the overall micro-Doppler signature. Moreover, in order to see the accuracy of velocity estimations computed from STFT and MUSIC spectrograms, the estimations using the second method of weighted power are compared as shown in Figure 7.

The total distance is computed from these velocity estimations and is found to be $11.34m$ (estimation error of 5.5%) for the STFT based spectrogram and $12.34m$ (estimation error of 2.83%) for the MUSIC based spectrogram. This result shows that the MUSIC based spectrogram outperforms the STFT on average. However, there is no significant difference between the two methods because the estimation methods in Section V are not much affected by frequency resolution.

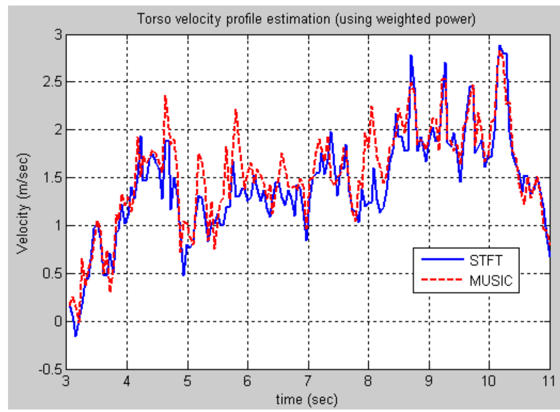

Figure 7. Torso velocity estimations comparison

VIII. Conclusion

Human activity monitoring and classification has important applications in a variety of fields. One of the major parameters that help to distinguish different human activities is the velocity profile of the translational human motion. Moreover, the estimated translational velocity profile, like the one shown in Figure 6, contains rich information about a person's activity such as: direction of motion, the time when the person started and stopped moving, the distance moved, whether there was a fast deceleration due to falling, whether everything was static, etc. Radars are suitable off-body sensors that can be used to measure velocity profile. However, the Doppler frequency pattern obtained from radars working in indoor environment is quite complex. This is due to the presence of multipath in indoor environment and the fact that the human body consists of rigid body parts of different RCS and velocity profiles. Therefore, joint time-frequency estimation methods such as STFT and MUSIC are required to extract the Doppler frequency pattern from the signal. It is shown that the MUSIC based spectrogram not only provides a resolved spectrogram showing the contribution of each component but also results in lower estimation error. Two methods (maximum power and weighted power methods) were suggested for estimating the velocity profile from the spectrogram. The maximum power method is error-prone due to the need for a threshold as its performance depends on the choice and accurate estimation of the threshold value. In the absence of image frequencies (outdoor environment for instance), the weighted power method is a more suitable method. However, it is found that both methods are able to estimate the translational velocity profile with an accuracy that is good enough for the applications concerned.

It is evident that extracting velocity profiles of each part of the body (Figure 1) from the analogous MUSIC spectrogram pattern (Figure 5) will be a very big step that can enable activity classification. However, this requires research on how to identify the frequencies in a spectrogram column and how to match those with the corresponding frequencies in the consecutive column. A major limitation of the velocity estimation methods discussed so far is that only the radial component of the velocity is being perceived and estimated by the radar. One way to achieve a better estimation is by combining information from two or more radars adjusted to monitor distinct directions. The velocity estimation methods discussed in this paper assume that there is a single mover in the monitored environment. In applications where this is not acceptable, it is essential to be able to discriminate and track the velocity profiles of multi-movers. In future work, strategies to discriminate the velocity profile of multi-movers in a given environment will be considered.

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