Full Duplex Backscatter

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ABSTRACT

This paper asks the following question: could we transform the radios found in our personal gadgets into powerful multi-purpose scanning devices that can detect and locate tumors, guns, buried human bodies, a la the Star Trek Tricoder? Our key insight is that if radios could measure the backscatter of their own transmissions (i.e. reflections from the environment of their transmissions), then Tricorder-style powerful object detection and localization algorithms could be realized. In this paper we focus specifically on backscatter measurement, we describe novel circuits and algorithms that can be added to existing radios to enable them to accurately and concurrently receive and disentangle their own transmissions' reflections and infer its properties.

Categories and Subject Descriptors

C.2.1 [**Computer Communication Networks**]: Network Architecture and Design—*Wireless communication*

General Terms: Algorithms, Design, Performance, Theory

1. INTRODUCTION

Could we use our phones to detect and locate tumors inside our body [14, 24] ? Could we use our phones to detect and locate concealed guns? Could we use our phones to build indoor guidance systems that can detect and locate walls and objects? Could we use our phones to detect and locate where people might be trapped under a rubble after an earthquake, or where mines might be hidden under the ground? More generally, could we turn our phones from simple computing and communication devices into powerful scanning devices, a la the Star Trek Tricoder [5]?

We believe that it may be possible to add this functionality (with appropriate hardware changes) to WiFi, 3G, LTE, 60GHz, etc. radios that are already present in our phones and turn them into powerful multi-purpose scanning devices. Further, in many cases, the scanning could be accomplished

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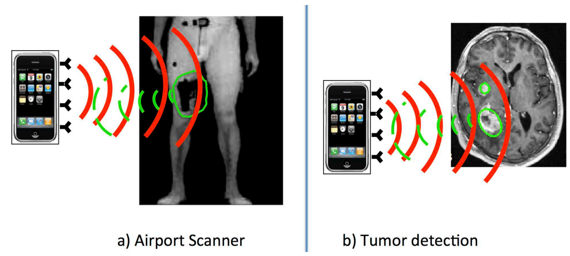

Figure 1: Applications of full duplex backscatter: On the left, we see how guns reflect almost all the signal whereas the rest of the body lets it through. We can use this to detect whether and where the gun is located, airport scanners work on this principle. The same idea applies to detecting tumors since tumor tissue reflects whereas normal tissue mostly allows signals to pass through, the main difference is that tumors are smaller objects compared to guns.

while these radios are being used for their regular purpose of communication. Our key insight is that we can mine the backscatter that radio transmissions inevitably produce for detection and location of different objects ranging from tumors to guns to bodies. Radio waves get reflected by the environment around them and many of the reflections arrive back at the transmitter. The strength and other spectral properties (phase) of the reflection depends on the reflecting object. For example, biological studies have shown that tumor tissue has higher dielectric constant than normal tissue by factor of 5 [13, 8, 22, 15]. Similarly airport scanners work on the principle that metal objects such as guns have higher reflection coefficient compared to the human body as seen in Fig. 1 (the reflection coefficient of human body and metal differ significantly [2], i.e., metal reflects almost everything, while the human body almost lets the entire signal through and reflects little). In fact, expensive medical imaging equipment and airport scanners use the same principle to detect tumors and scan for security [3, 9].

However, if we could mine the backscatter of transmissions from radios to accurately estimate the properties of each reflector (the strength of the reflection, the delay experienced by the reflected signal with respect to the radio transmitter, and the angle of arrival of the reflection), then we could potentially build applications on top that use that information to detect specific objects and also locate them. For example, armed with the strength of the reflection and the relative delay from the reflector, we can estimate what the dielectric properties of the reflector is, and use that to infer the nature of the object. Further using the delay and angle of arrival information we can potentially locate where the reflecting object is located. Accuracy can be further improved by collecting the same measurements from multiple locations and combining them with appropriate algorithms.

The first key challenge however is detecting and measuring backscatter itself. The signal that is being transmitted leaks over to the radio's receiver and causes a large amount of self-interference, which could completely drown out the backscatter [7, 19, 11, 6, 20, 10, 17, 18] because of the limited *dynamic range* of practical radios. Second, the different components in the backscatter itself could act as self-interference to each other. For example, if there is a nearby reflector, the corresponding reflection will be strong compared to a reflector that is farther out, which in some case may be as much as 50-60dB. With such strong interference from the nearby reflector, the weak reflection might again get swamped out. To be able to detect all the different components in the backscatter accurately, we need to be able to selectively remove self-interference and measure the individual reflections.

The second challenge is estimating the parameters of each reflection (amplitude, delay and angle of arrival [23]) from a signal that contains a larger number of reflections combined together into one composite signal. Further, many of the reflections could be quite closely spaced and well within the sampling interval of the receiver. For example, we could have two reflections that are spaced 1ns apart (or $\frac{1}{2}$ foot apart in distance), but with a radio with a typical sampling rate of 40Msps, two consecutive digital samples themselves are spaced 25ns apart. In other words, we have to get time resolution of much smaller values than even what our sampling itself can provide. One naive option could be to increase the sampling rate, for example to have 1ns resolution we need a ADC sampling rate of 1GHz. However such high-rate ADCs are prohibitively expensive both in terms of cost as well as power consumption and are infeasible for most radios.

In this paper, we propose a novel technique that solves both the problems of limited dynamic range and sampling rates. We first propose a progressive self-interference cancellation technique that selectively and incrementally cancels each component in the backscatter, starting from the leakage component to the first strongest reflector and so on, to the weaker reflectors. The cancellation also benefits backscatter measurement, because removing each successive component of the backscatter improves the accuracy with which we can estimate the remaining components (since there is less interference, lesser number of components to estimate and higher precision on the measurement). This successive cancellation and estimation algorithm helps us accurately estimate the strength, delay and angle of arrival of each backscatter component. Second, even if two reflections are closely spaced in time and strength because the relative distances from the transmitter are close, they are quite likely to have a different spatial orientation and hence the angles of arrival of the two reflections will be quite different. Hence even if two reflections are within the sampling interval, we leverage the fact that many radios have multiple antennas that allow us to disentangle the reflections in the spatial dimension and accurately estimate the backscatter parameters.

In a nutshell, this paper is a first and quite preliminary step towards realizing the vision of a Tricoder. It lays the first building block of being able to measure backscatter, but much work remains. We plan to research the algorithms that can operate on these measurements to detect and locate different objects. We also plan to research what frequencies are needed for different applications, for example 2.4GHz and 5GHz radios are the right frequencies for detecting large objects such as metals and human bodies, but we likely need 60GHz radios to detect small objects such as tumors. We also plan to research the hardware implications on radio design to support such scanning capabilities. In summary, we believe that many challenges remain and some might even require hardware modifications, but the prospect of adding such scanning capabilities to our personal devices and making them cheaply and commonly available can be quite impactful.

2. PROBLEM

We build up the basic problem definition for detecting and measuring backscatter using a simple toy example as shown in Fig.2. The text focuses on estimating delays and reflection amplitudes for brevity, but the same development can be applied to estimating angles of arrival too. This scenario has a strong and a weak reflection in the backscatter at delays of τ_1, τ_2 respectively and the corresponding strengths of the reflected signals are α_1, α_2. In other words, if we transmitted signal $x(t)$, the backscatter is given by $\alpha_1 x(t-\tau_1) + \alpha_2 x(t-\tau_2)$. It helps to think in terms of the channel response which the transmitted signal has gone through. In the above example, its a simple delayed and attenuated reflection whose impulse response is given by $\alpha_1 \delta(t-\tau_1) + \alpha_2 \delta(t-\tau_2)$. Note that in practice reflections get more attenuated as delay increases because the signal with larger delay has travelled a longer distance.

This model is valid only when the receiving radio has infinite bandwidth. However, our radios have limited bandwidth at the receiver, for example a typical WiFi radio in the 2.4GHz band has 20MHz bandwidth. Conceptually this means that the received backscatter signal can be measured only within a bandwidth (say B) corresponding to the sampling rate of the receiver. In other words the receiver acts as a bandpass filter. So the overall channel response that the transmitted signal has gone through before we see the backscatter in the digital domain is given by the convolution of the receiver filter response with the reflection impulse response, which can be expressed mathematically as [1], $h(t) = \sum_{k=1}^{2} \alpha_k \mathrm{sinc}(B(t-\tau_k))$. Fig. 3 shows the overall band-limited channel response of the composite filtered and delayed impulse responses. The figure also shows the individ-

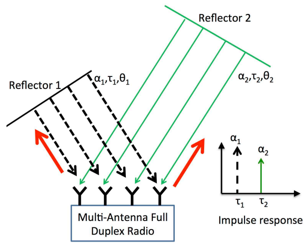

Figure 2: Multi-antenna system, receiving two backscatter reflections at different delay, angle, and amplitude.

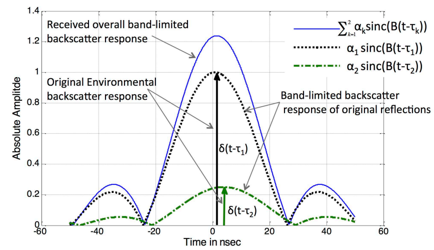

Figure 3: The original reflections from the environment are closely located impulses. After going through the band-limited receiver, the impulses get converted to sinc functions, and the overall response is the sum of the two sincs. Note how similar the overall response looks to the sinc corresponding to the strong reflection, and this is the reason two closely spaced reflections are hard to disentangle.

ual filtered response of impulses $\alpha_1\delta(t-\tau_1)$ and $\alpha_2\delta(t-\tau_2)$. Notice how the combined channel response is similar to the scenario where there is only a single reflection at τ_1. This is because the second reflection at τ_2 is closely spaced in time and is also very weak compared to the first reflection, and therefore does not contribute significantly to the overall response. The challenge therefore is to be able to accurately resolve individual responses at τ_1 and τ_2 from the combined response in scenarios where they are separated in time by interval smaller than the sampling interval (sub-sampling).

Further, while we have used a scenario with two reflections to develop the problem, in practice the backscatter signal will have multiple reflections at various delays and attenuations. So the actual impulse response of L reflection components for an infinite bandwidth system is given by, $h_\infty(t) = \sum_{k=1}^{L} \alpha_k \delta(t-\tau_k)$. Therefore, after the reflected signal is band-limited to bandwidth B, the overall channel response has the following complex structure,

$$h(t) = \sum_{k=1}^{L} \alpha_k \mathrm{sinc}(B(t-\tau_k)). \qquad (1)$$

A further complication is that the reflection coefficients exhibit a heavy tailed distribution in strength shown in Fig. 4. The strongest backscatter component is the signal that is directly leaking through from the transmit chain to the receive chain, the next strongest backscatter component is the closest first reflection and so on. Further the first few leaked strongest components can be nearly 70-80dB stronger than the other weak multi-path components. A typical WiFi receiver has a dynamic range of 60dB (i.e the highest ratio between the strongest and weakest signals that can be received without significant distortion of the weakest signal). Consequently, the strong backscatter components can quite easily drown out the weaker backscatter components. In summary, our goal is to determine all the attenuations α, delays τ, (and also the angle of arrivals (AoA) θ, though we omit it from the equation below for brevity) of the individual backscatter components accurately from the sampled, band-limited backscatter despite the limited dynamic range and finite bandwidth of commodity radios. The discrete time version of the impulse response can be written as,

$$h[n] = \sum_{k=1}^{L} \alpha_k \mathrm{sinc}(B(nT_s-\tau_k)). \qquad (2)$$

This model is valid for a single transceiver, we will refine this model further to include AoA for a MIMO system in Sec. 3.3.

3. DESIGN

Our design provides accurate backscatter measurement with commodity radios by designing two novel techniques to tackle the limitations of low dynamic range and finite bandwidth available in commodity radios. Before we describe them in detail, we first set up the basic measurement problem and describe how we solve it. The algorithm starts by measuring the overall channel response that the backscatter has gone through. This is classic channel estimation that every receiver performs [1]. We omit the details here, but the rest of this paper will assume that we know the $h[n]$, where $y[n] = x[n] * h[n]$. Note that this $h[n]$ is the composite overall response, but our goal is to break it down into the form where we can tease out the individual $\tau_i, \alpha_i, \theta_i$ values corresponding to each of the reflections that make up the overall backscatter channel. More formally, from the previous section we can show that the goal is to deconstruct the $h[n]$ as given in Eqn. 3.

If we can find the solution, we will have found all the parameters of the backscatter. The above problem is nonlinear because the sinc terms in the optimization problem are non-linear. Further, the problem is not convex. So our basic approach is to solve this problem piece-wise. In other words, we focus on a small region in the variable space $\delta\tau, \delta\alpha, \delta\theta$, approximate the sinc functions in that region by straight lines, and solve the resulting convex optimization problem. We then compare the residual error and repeat until successive iterations of the algorithm does not reduce the error any further. Similar work on deconstruction of continuous time channel model have been done in [16], but the problem that we are trying to tackle takes the finite bandwidth and the discrete time nature of the channel response into consideration.

3.1 Tackling Limited Dynamic Range

The challenge is that some of the reflections in the backscatter may be significantly stronger than others. For example if there is a reflector 10cm away from the transmitter and another 10m away, the difference in signal strengths of these two components can be as high as 60dB. Commodity

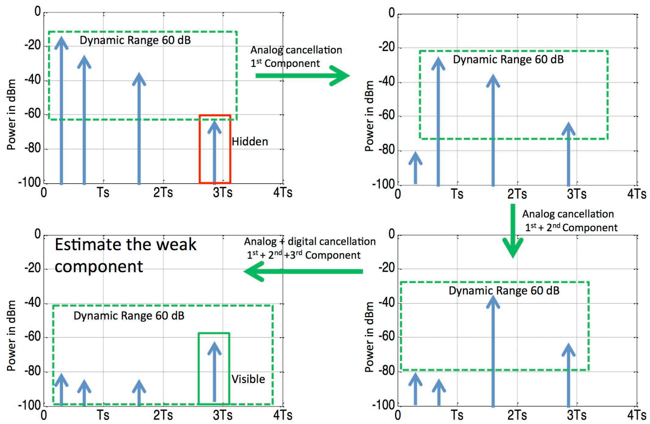

Figure 4: Limited dynamic range of transceiver and the result of Progressive interference cancellation (PIC) algorithm.

WiFi radios have a typical dynamic range of 60dB, which would imply that the weaker reflection would get completely buried. Second, even if the weaker reflection is within the dynamic range, its not being represented with many bits and hence there is higher quantization noise. While the strong components can be estimated reasonably accurately, the weaker components cannot be and inevitably this leads to inaccurate backscatter parameter estimation.

Our key insight here is that accuracy can be improved if we can progressively remove the strongest backscatter component and allow the estimation algorithm to operate on the remaining components as shown in Fig. 4. By removing the stronger component, the receivers dynamic range can be used to sample the weaker components with higher resolution and thus prevent them from being washed out or distorted. Once these are estimated, remove the strongest remaining component and run the estimation algorithm on the remaining backscatter signal. The algorithm recursively repeats until all components are estimated. More intuitively, we are progressively canceling strong backscatter components and improving the accuracy of estimation for the remaining components.

The challenge therefore is to selectively eliminate backscatter components by canceling them. Further the cancellation has to be implemented in analog before the receiver, since otherwise dynamic range will again be limited. To implement this, we build on prior work in self-interference cancellation and full duplex [7]. We reuse the analog cancellation circuit design proposed in this prior work. However we make one key contribution. The goal of the prior work was to cancel as much of the self-interference (or backscatter) as possible. Our goal is to be selective and progressive, i.e. cancel the backscatter components in a controlled manner one by one. To accomplish this we build on the same estimation algorithm described above. We use the initial estimates to find a coarse estimate of where the strong backscatter components are located. We then tune the analog cancellation circuit to only cancel these components by controlling the delay taps in the circuit to straddle the delay of these strong components. After running the estimation algorithm on the remaining backscatter signal, we retune the analog cancellation to cancel the next strongest component and repeat the process. We will refer to this cancellation block as Progressive self-Interference Cancellation (PIC) in rest of the paper.

Note that analog cancellation can achieve a maximum of 70dB of cancellation, so we cannot keep progressively canceling backscatter beyond a particular level. However after such cancellation, assuming a receiver dynamic range of at least 60dB, we can easily estimate the remaining components. Further, we can repeat the same cancel and estimate procedure in digital by selectively canceling the residual backscatter components using the digital cancellation algorithm described in [7].

3.2 Tackling Limited Sampling Resolution

The second challenge is that commodity radios have limited sampling rates since having extremely high sampling rates is prohibitively power hungry [21]. As we saw in Fig. 3, the limited bandwidth creates a complex response which is a sum of shifted sinc functions. Further, the width of the sinc increases with decreasing bandwidth. Consequently, the ability to estimate the actual delay and amplitude of the backscatter reflections also reduces. This problem is worse when there are multiple reflections that are within the sampling period. For example, for a 40Msps, the sampling resolution is 25ns. But 25ns corresponds to a distance separation of 25 feet, and we could easily have two backscatter reflections within 25 feet. Can we tease apart such close backscatter components when we are not even getting digital samples that are closely spaced enough?

In general, the closely spaced reflections lead to a degenerate system of equations. For example, when the reflections at two delays τ_1 and τ_2 are closely spaced, the difference in sample values of the corresponding sinc functions are very small and therefore the observations are highly correlated. As more reflections are closely spaced within a sampling period, the problem of uniquely reconstituting them becomes more difficult. Consequently, reconstruction error increases since the optimization algorithm struggles to find a good fit. In practice, we found that even if there were two very closely spaced reflectors in time (i.e. the relative delays from the transmitter to the two reflectors were within a sampling period of each other), they could still be deconstructed accurately as long as their spatial orientations relative to the transmitter are different (i.e. their backscatters have different AoAs). However closely spaced backscatter reflections in both space and time are harder to disentangle.

To tackle this problem, we take advantage of the spatial dimension. For example, if the radio has four antennas and the two closely spaced reflections are arriving at angles θ_1 and θ_2 respectively, then the two reflections can be distinguished in the spatial dimension because they will exhibit different phases at the different antennas. The reason is that because of the different angles of arrival, the two reflections will travel different distances which translates to a phase difference across successive antennas. By incorporating this constraint into the optimization problem, we can disentangle closely spaced reflections within a single sampling period. In practice we find that with 4 antennas (expected to be found in the next generation WiFi radios), we can distinguish up to 4 closely spaced reflections within a single sampling period. In effect we get the same performance as an ADC that has four times the sampling bandwidth while still using cheap commodity radios.

3.3 Formal Algorithm

In this section we provide a brief description of the formal mathematical model, problem and our algorithm. The composite backscatter channel as seen by the mth receiver in the MIMO antenna array can be modeled as,

$$h_m[n] = \sum_k \alpha_k e^{i(\nu_k+\gamma_{mk})}\,\mathrm{sinc}(B(nT_s - (\tau_k + \frac{\gamma_{mk}}{2\pi f_c}))) \tag{3}$$

,where $\gamma_{mk} = \frac{2\pi}{\lambda}(m-1)d\sin\theta_k$ is the added phase shift experienced by the kth reflection at the mth receiver relative to the first receiver when the reflected signal arrives back at θ_k AoA, $\alpha_k e^{i\nu_k}$ is the complex attenuation for the kth reflection, and τ_k is its corresponding delay. The constant f_c is the carrier frequency with wavelength of λ, and d is the distance between the successive receiving antennas in the array. Theoretically $h_m[n]$ can be of infinite length, but in practice the sinc function decays to very small values for large values of n. Thus the channel can be modeled by a finite length vector with n taking value in the range of $[-N, N]$.

As discussed before, the composite finite-length linear channel $h_m[n]$ can be estimated by deconvolving the received samples with known preamble samples. Once the composite linear channel has been estimated, we can estimate the parameters of the constituent backscatter components by solving the following optimization problem.

$$\begin{array}{ll} \text{minimize} & \sum_m \sum_n \|h_m[n] - \tilde{h}_m[n]\|^2 \\ \text{subject to} & \tau_k \geq 0, \alpha_k \leq 1, \\ & \theta_k \in [\frac{-\pi}{2}, \frac{\pi}{2}], \nu_k \in [0, 2\pi], \\ & k = \{1, \ldots, L\}, n = \{-N, \ldots, N\}, \\ & m = \{1, \ldots, M\} \end{array} \tag{4}$$

,where $\tilde{h}$ is the estimated linear channel response obtained by the deconvolution of received samples with a know preamble, M is the number of antennas in the array, and L is the total number of reflected backscatter components.

This optimization problem is non-convex and is not known to have a global solution. Instead, we solve this problem approximately by finding a locally optimal solution. To this end we use a heuristic known as Sequential Convex Programming (SCP) [4], where all the non-convex functions are replaced by their convex approximation and then we solve the resulting convex problem in an iterative manner until a reasonable solution is achieved. One simple approach to convert (4) into a convex problem is to approximate (3) by a linear function. We have followed this approach in this paper, it has to be noted however that a more sophisticated convex-approximation of (3) could potentially result in better overall accuracy of estimation. Due to the limited dynamic range of the ADC used in the receiver, stronger backscatter components mask the weaker ones. In the initial step, the algorithm finds the parameters corresponding to the strong backscatter components and then passes that information to the progressive self-interference cancellation (PIC) block. The PIC block will cancel these reflections, which will allow the receiver AGC to increase gain for the weak backscatter components which can now become detectable due to the cancellation of the strong reflections. We can then run the estimation algorithm again to estimate the parameters of the weak components and send back that information to PIC for further cancellation.

```
1: Begin in the first time window w_0
2: Estimate parameters α, τ, θ for reflectors in window w_0 by solving the
   optimization problem given by Eqn. 4
3: repeat
4:     Pass the estimated parameters of all reflectors in the past windows
       w_{p-1} ... w_0 to analog PIC block for cancellation
5:     Estimate parameters α, τ, θ for reflectors in the current window w_p by
       solving the optimization problem given by Eqn. 4
6:     Advance window to w_{p+1}
7: until Parameters for reflectors in the last window w_P has been estimated by
   forward estimation
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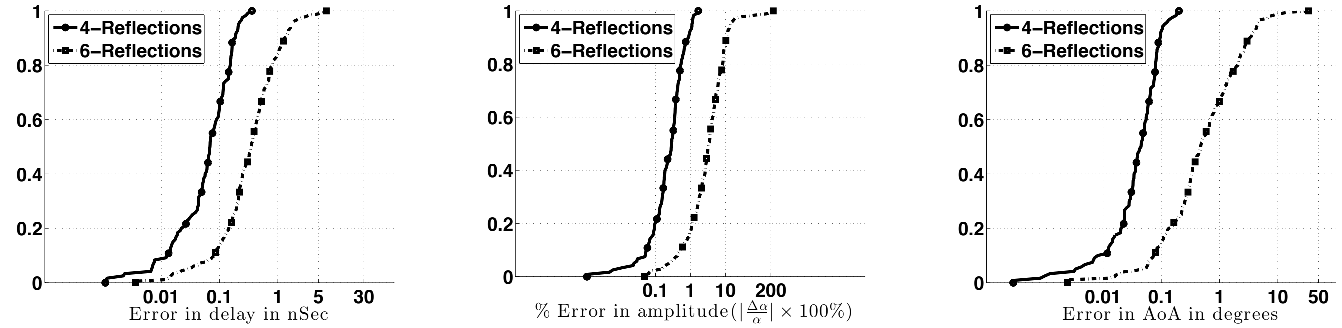
Algorithm 1: Progressive steps in backscatter channel parameters estimation

Usually the strength of the backscatter components are weaker for larger values of the delay τ. Hence we can run the estimation algorithm by partitioning the range for the variable τ into several non-overlapping windows. The algorithm begins by estimating parameters for the reflections in the first time window then passes that information to the PIC. After the cancellation of these components advance the window one step into the future and then estimate the parameters in that range and pass that information to PIC for cancellation. This process can repeat multiple times until all the backscatter components have been detected in the forward time direction. We can set a reasonably high value of τ beyond which the backscatter components present are very weak; this maximum value depends on the application and the environment [12]. The major steps in this estimation process are described in the Algorithm 1 .

4. PRELIMINARY EVALUATION

In this section we present preliminary results to show that accurate backscatter measurement is possible using future commodity radios. First, we show via a hardware implementation on off-the-shelf WARP radios that progressive cancellation is possible. Next we show via realistic simulations in matlab that backscatter can be measured accurately using our parameter estimation algorithm in conjunction with progressive self-interference cancellation. We use simulation because it is otherwise hard to test the accuracy, as we have no way of knowing ground truth with a hardware experiment.

Progressive Self-Interference Cancellation: We created an emulated backscatter setup with WARP hardware with three reflection components. We use a standard OFDM baseband



(a) CDF of accuracy of our estimation algorithm for delay parameter τ.

(b) CDF of accuracy of our estimation algorithm for the amplitude of the reflections α.

(c) CDF of accuracy of our estimation algorithm for AoA of the different reflections θ.

Figure 5: **Performance of algorithm.**

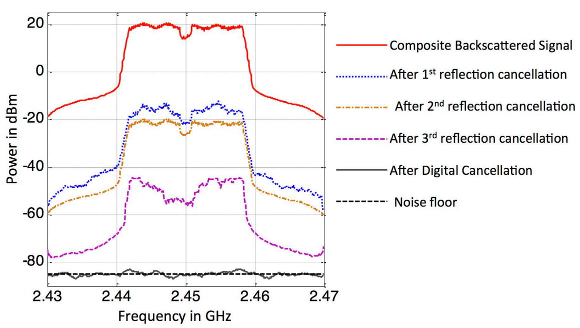


Figure 6: Frequency domain view of progressive self-interference cancellation of three strong backscatter components.

with 20MHz bandwidth to create the transmitted signal. Next, we split the signal at the TX output of the WARP radio into three wires of different lengths to emulate a multipath backscatter signal with increasing delays and attenuations.

The goal is to show that we can tune our analog cancellation circuit to only cancel the first component and leave the other two components alone. We use our estimation algorithm to compute the coarse delay experienced by the first component. We use this delay estimate to tune our analog cancellation circuit to cancel the self-interference signal located around that estimated coarse delay. Fig. 6 shows the results before and after progressive cancellation.

The composite backscatter signal is made up of three strong reflections in addition to several smaller reflections. After the first step of progressive self-interference cancellation, the first component is significantly reduced, while the other two strong components with higher delays are hardly affected. Next, we use the same algorithm to also cancel the second component and preserve only the third component. Notice also that the first and second components are close in amplitude and delay (in fact the delay difference is within the sampling interval), yet the technique is able to selectively cancel the first and second reflections one after the other and leave the last one alone. A subsequent analog cancellation step allows us to cancel the three strongest backscatter components and that also hits the limit of what analog cancellation is capable of (70dB). However, the same technique (PIC) can be applied to cancel the remaining backscatter components progressively via digital cancellation. The digital cancellation step improves estimation accuracy, but does not improve the dynamic range.

Overall Accuracy: We turn to matlab simulation to check overall accuracy of our estimation algorithm with PIC. To simulate cancellation we assume that after the strongest backscatter component is coarsely estimated, it can be cancelled out. The simulation assumes 4 antenna system, with the sampling rate of 40Msps (so the sampling period is 25ns). The backscatter channel has 4 and 6 reflections, where upto 3 reflections could be spaced within the sampling period of 25ns. We apply the estimation and PIC in an iterative fashion as described in Algorithm 1. The CDF of the estimation for the parameters α, τ, and θ are shown in figure (5a), (5c), (5b).

As we can see, we achieve a median accuracy of 0.4ns for the backscatter delays in spite of having a sampling period of 25ns. Similarly we have 1% accuracy in estimating the strength of the backscatter reflections, and a median accuracy of angle of arrival estimation of 0.5 degrees. With such accuracy, we could probably detect the object type with high accuracy since dielectric properties differ vastly for different objects.

5. CONCLUSION

This paper presents the first step in our research agenda to turn everyday commodity radios into powerful multi-purpose scanning devices. We show how by collecting, measuring and mining the natural backscatter than happens when radios transmit, we can potentially detect and locate objects with high accuracy. We show how we can build on prior work in self-interference cancellation to enable commodity radios to clean measure backscatter and estimate its properties. We are currently working on improving these algorithms as well as designing medical and security applications that take advantage of the backscatter measurements for tumor and gun detection.

6. REFERENCES

[1] *David Tse , Fundamentals Wireless Communications*. http://www.eecs.berkeley.edu/~dtse/Chapters_PDF/Fundamentals_Wireless_Communication_chapter2.pdf.

[2] *Dielectric Properties of Body Tissues*. http://niremf.ifac.cnr.it/tissprop/htmlclie/htmlclie.htm#atsftag.

[3] *FDA, Medical Imaging*. http://www.fda.gov/Radiation-EmittingProducts/RadiationEmittingProductsandProcedures/MedicalImaging/MedicalX-Rays/ucm115317.htm.

[4] *Sequential Convex Programming*. http://www.stanford.edu/class/ee364b/lectures/seq_slides.pdf.

[5] *Star Trek Tricoder*. http://en.wikipedia.org/wiki/Tricorder.

[6] F. Adib and D. Katabi. See through walls with wifi! In *Proceedings of the ACM SIGCOMM 2013 conference on SIGCOMM*, SIGCOMM '13, pages 75–86, New York, NY, USA, 2013. ACM.

[7] D. Bharadia, E. McMilin, and S. Katti. Full duplex radios. In *Proceedings of the ACM SIGCOMM 2013 conference on SIGCOMM*, SIGCOMM '13, pages 375–386, New York, NY, USA, 2013. ACM.

[8] G. N. Bindu, S. J. Abraham, A. Lonappan, V. Thomas, C. K. Aanandan, and K. T. Mathew. Active microwave imaging for breast cancer detection. *Progress In Electromagnetics Research, Vol. 58, 149-169, 2006.*

[9] A. Cavoukian. Whole body imaging in airport scanners: Building in privacy by design. http://www.ipc.on.ca/images/Resources/wholebodyimaging.pdf.

[10] M. Duarte, C. Dick, and A. Sabharwal. Experiment-driven characterization of full-duplex wireless systems. *CoRR*, abs/1107.1276, 2011.

[11] M. Duarte and A. Sabharwal. Full-duplex wireless communications using off-the-shelf radios: Feasibility and first results. In *Forty-Fourth Asilomar Conference on Signals, Systems, and Components*, 2010.

[12] V. Erceg, L. Schumacher, P. Kyritsi, and et al. Tgn channel models. *Tech. Rep. IEEE P802.11, Wireless LANs, Garden Grove, Calif, USA*, 2004.

[13] E. Fear, S. Hagness, P. Meaney, M. Okoniewski, and M. Stuchly. Enhancing breast tumor detection with near-field imaging. *Microwave Magazine, IEEE*, 3(1):48–56, 2002.

[14] E. Fear, X. Li, S. Hagness, and M. Stuchly. Confocal microwave imaging for breast cancer detection: localization of tumors in three dimensions. *Biomedical Engineering, IEEE Transactions on*, 49(8):812–822, 2002.

[15] E. Fear and M. Stuchly. Microwave detection of breast cancer. *Microwave Theory and Techniques, IEEE Transactions on*, 48(11):1854–1863, 2000.

[16] B. Fleury, M. Tschudin, R. Heddergott, D. Dahlhaus, and K. Ingeman Pedersen. Channel parameter estimation in mobile radio environments using the sage algorithm. *Selected Areas in Communications, IEEE Journal on*, 17(3):434–450, 1999.

[17] B. Guo, Y. Wang, J. Li, P. Stoica, and R. Wu. Microwave imaging via adaptive beamforming methods for breast cancer detection. *Progress In Electromagnetics Research, Vol. 1, 350-353, 2005.*

[18] S. S. Hong, J. Mehlman, and S. Katti. Picasso: flexible rf and spectrum slicing. In *Proceedings of the ACM SIGCOMM 2012 conference on Applications, technologies, architectures, and protocols for computer communication*, SIGCOMM '12, pages 37–48, New York, NY, USA, 2012. ACM.

[19] M. Jain, J. I. Choi, T. Kim, D. Bharadia, S. Seth, K. Srinivasan, P. Levis, S. Katti, and P. Sinha. Practical, real-time, full duplex wireless. MobiCom '11, pages 301–312, New York, NY, USA, 2011. ACM.

[20] A. Sahai, G. Patel, C. Dick, and A. Sabharwal. On the impact of phase noise on active cancellation in wireless full-duplex. *CoRR*, abs/1212.5462, 2012.

[21] T. Sundstrom, B. Murmann, and C. Svensson. Power dissipation bounds for high-speed nyquist analog-to-digital converters. *Circuits and Systems I: Regular Papers, IEEE Transactions on*, 56(3):509–518, 2009.

[22] A. Surowiec, S. Stuchly, J. Barr, and A. Swarup. Dielectric properties of breast carcinoma and the surrounding tissues. *Biomedical Engineering, IEEE Transactions on*, 35(4):257–263, 1988.

[23] J. Xiong and K. Jamieson. Arraytrack: a fine-grained indoor location system. In *Proceedings of the 10th USENIX conference on Networked Systems Design and Implementation*, nsdi'13, pages 71–84, Berkeley, CA, USA, 2013. USENIX Association.

[24] H. Zhang, S. Y. Tan, and H. S. Tan. A novel method for microwave breast cancer detection. *Progress In Electromagnetics Research, Vol. 83, 413-434, 2008.*