Energy Efficient Antenna Arrays for Indoor Three-dimensional Microwave Imaging

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Abstract—The effect of antenna array size, transmit power, component noise and other parameters on the performance of microwave imaging algorithms is characterized, with the focus on indoor applications where objects are in the array near-field. A large antenna array testbed was built to capture three-dimensional images of objects in the 17-20GHz band, and the quality of these images evaluated. The standard range-migration algorithm, the modified single-transmitter range-migration algorithm and a novel Doppler imaging algorithm were all compared. A new figure of merit was also developed to compare how efficiently these algorithms can create an image of given quality and size. It was found that these algorithms are able to produce good quality images at extremely low transmit power levels and with noisy transceivers, leading to a methodology for designing energy and cost efficient microwave imaging systems.

Index Terms—Microwave imaging, antenna arrays, Doppler measurement, millimeter wave technology, energy measurement.

I. INTRODUCTION

Near-field microwave imaging based on the range migration algorithm (RMA) uses an array of antennas to create images from reflected radio-frequency (RF) waves. Generally, one or more antennas illuminate the scene with an RF signal while the other antennas record the reflections. In this work, a two-dimensional planar antenna array, sweeping from 17 to 20 GHz, is used to create three-dimensional images of static and moving objects in the near-field. While microwave imaging using RMA is not new [1], it has historically had limited practicality due to the high cost of the large numbers of antennas and radio transceivers required to build the arrays. However, with the decreasing cost of multi-GHz transceivers, driven primarily by the wireless communication industry, it may now be feasible to build such imaging systems.

Looking forward, we believe it will soon be viable to build wall-size antenna arrays for microwave imaging by embedding the antennas and transceivers into large flexible sheets of material, such as wallpaper. For example, a large array of antennas could be printed using conductive ink [2] and connected to bare die RF transceivers embedded directly within the wallpaper. Such a system could be mounted unobtrusively within any room in a building, enabling applications such as gesture recognition, long-term health monitoring including fall and gait monitoring, and user identification in the smart home.

For these large-scale imaging arrays to be feasible, they need to be as energy efficient as possible, due to the large number of RF transceivers. This paper therefore experimentally characterizes the effect of near-field microwave imaging algorithm selection and antenna array parameters on energy consumption and image quality, using a generic imaging testbed. In particular, this paper focuses on the limits of energy and cost efficiency for these antenna arrays without sacrificing image quality. These results allow us to develop a new figure of merit for microwave imaging systems and a methodology for designing these systems to be as energy efficient as possible.

Since a major application of this technology is imaging people as they move, work was also done to (a) image human hand phantoms and (b) design a new variant of the RMA algorithm that images moving objects and measures their velocity from their Doppler shift.

This paper expands on our previous work [3] by shifting the focus to energy consumption. While the original paper simply characterized the effects of imaging system parameters on image quality, this paper adds a new analysis of how these parameters affect energy consumption. Furthermore, this paper introduces a novel figure of merit for specifying the energy efficiency of microwave imagers, and uses this to develop a methodology for designing energy efficient imaging systems. This paper also describes the theoretical formulation and practical implementation of the range migration algorithms in more detail, including how to deal with physical imperfections.

II. REVIEW OF THE RANGE MIGRATION ALGORITHM

The range migration algorithm, also known as backward-wave reconstruction [4], forms images by coherently integrating the reflected wave over a synthesized aperture. It is commonly used in microwave imaging because (a) it compensates for the curvature of the wavefront and hence can be used for near-field imaging, and (b) it is based on computationally efficient fast-Fourier transforms. The RMA algorithm was first used in geophysics and radar for 2D imaging [5], and later extended to planar antenna arrays [1] [6], allowing 3D images to be formed. This algorithm is outlined below.

The variables and co-ordinate system are defined as follows:

• The antenna array lies in the xy-plane at $z = Z_0$.
• $f(x, y, z)$ is the reflectivity function of the scene, i.e. the image we are trying to recreate.
• $s(x_a, y_a, \omega)$ is the complex reflection recorded at antenna position $(x_a, y_a)$ and at frequency $\omega$, when both the transmitting and receiving antennas are colocalized.
• $k = \frac{\omega}{c}$ is the wavenumber and $k_x, k_y, k_z$ are the spatial frequency variables of $x, y, z$. 
A. Colocated Range Migration

To create an image, the transmitting antenna illuminates the scene with a monochromatic RF wave. The colocated receiving antenna records the complex reflected signal, i.e., \( s(x_a, y_a, \omega) \). The transmitting antenna then transmits the next frequency step. This process is repeated for the next transmit/receive antenna in the array.

The round-trip phase delay from antenna at \((x_a, y_a, Z_0)\) to point reflector in the scene at \((x, y, z)\) is:

\[
2k \times d \text{ where distance } d = \sqrt{(x-x_a)^2 + (y-y_a)^2 + (z-Z_0)^2} \tag{1}
\]

Attenuation effects due to path loss can be ignored, as they have little effect on the resulting image quality [6]. Therefore, if the point reflector at co-ordinate \((x, y, z)\) has reflectivity \(f(x, y, z)\), the response \(s\) recorded at the antenna at frequency \(\omega\) will be:

\[
s(x_a, y_a, \omega) = f(x, y, z) \times e^{-j2k\sqrt{(x-x_a)^2 + (y-y_a)^2 + (z-Z_0)^2}} \tag{2}
\]

By regarding the scene as a collection of point reflectors, the combined reflection recorded at antenna \((x_a, y_a, Z_0)\) is obtained by integrating equation 2 over the scene:

\[
s(x_a, y_a, \omega) = \int_\text{scene} f(x, y, z) \times e^{-j2k\sqrt{(x-x_a)^2 + (y-y_a)^2 + (z-Z_0)^2}} \, dx \, dy \, dz \tag{3}
\]

The square-root in the exponential term in Equation 3 makes the expression difficult to invert to obtain \(f(x, y, z)\). Fortunately, the exponential term describes a spherical wave, which can be expressed as a sum of plane waves [7]:

\[
e^{-j2k\sqrt{(x-x_a)^2 + (y-y_a)^2 + (z-Z_0)^2}} = \int_0^\infty e^{-j(k_x(x-x_a) + k_y(y-y_a) + k_z(z-Z_0))} \, dk_x \, dk_y \tag{4}
\]

By combining equations 3 and 4 and rearranging the order of the integrals, we obtain:

\[
s(x_a, y_a, \omega) = \int_0^\infty \left[ \int_0^\infty \int_0^\infty f(x, y, z) \times e^{-j(k_x(x-x_a) + k_y(y-y_a) + k_z(z-Z_0))} \, dk_x \, dk_y \right] \, dk_z \tag{5}
\]

The inner triple integral represents the 3D spatial Fourier transform of \(f(x, y, z)\), while the outer double integral can be expressed as the 2D inverse Fourier transform with respect to \((k_x, k_y)\). We therefore rewrite Equation 5 as:

\[
s(x_a, y_a, \omega) = FT^{-1}_2 \left\{ FT_3 \left\{ f(x, y, z) \right\} \right\} e^{j k_z Z_0} \tag{6}
\]

Inverting the Fourier transforms, we can reconstruct the original scene using:

\[
f(x, y, z) = FT^{-1}_3 \left\{ \Phi \left\{ FT_2 \left\{ s(x_a, y_a, \omega) \right\} \right\} e^{-j k_z Z_0} \right\} \tag{7}
\]

where \(\Phi\{\}\) is the Stolt transform [8] from \((k_{xa}, k_{ya}, \omega)\) space to \((k_x, k_y, k_z)\) space, according to:

\[
k_x = k_{xa} \tag{8}
\]

\[
k_y = k_{ya} \tag{9}
\]

\[
k_z = \sqrt{\frac{\omega^2}{c^2} - k_x^2 - k_y^2} \tag{10}
\]

The Stolt transform is only valid where \(4k_z^2 >= k_x^2 + k_y^2\), as this is required for the radiation condition. In practice, equation 7 is solved using discrete Fourier transforms. Therefore, the Stolt transform is implemented as an interpolation from one discrete co-ordinate system to the other. Since the mapping is non-linear and restricted (due to the radiation condition), multiple data points in the in the \((k_{xa}, k_{ya}, \omega)\) space may map to the same coordinate in \((k_x, k_y, k_z)\) space, and should be averaged [9], while some coordinates in \((k_x, k_y, k_z)\) space may not have any samples mapped to them and must be zero filled.

To most effectively fill the \((k_x, k_y, k_z)\) space with usable data, it was found useful to oversample in the \(k_z\) axis before applying the Stolt transform, so that number of non-zero data points remains the same after the transform. This oversampling is especially advantageous when the antennas are less than half a wavelength apart.

When capturing real data, the receiving antenna does not usually connect directly to the ADC, but rather via a cable and/or components. Therefore, the phase delay introduced by these components must be removed before processing. Assuming the cable has length \(L_{cab}\) and propagation velocity \(v_{cab}\), the phase delay of the cable is given by:

\[
\theta_{cab} = \frac{\omega L_{cab}}{v_{cab}} \tag{11}
\]

To remove this phase delay, we simply modify the colocated range-migration algorithm as follows:

\[
f(x, y, z) = FT^{-1}_3 \left\{ \Phi \left\{ FT_2 \left\{ s(x, y, \omega) e^{j \theta_{cab}} \right\} \right\} e^{-j k_z Z_0} \right\} \tag{12}
\]

B. MIMO Range Migration

While the equations described thus far assume colocated transmit and receive antennas, bistatic RMA variants have been developed [10] [11], allowing independent transmit and receive linear arrays. Zhuhe et al. [12] extended this work to independent MIMO-like planar arrays that can be used to create 3D images. Their algorithm is rederived here so that it matches the approach used for the colocated case.

When an antenna in the transmitting array transmits at frequency \(\omega\), every antenna in the receive array simultaneously records the reflected response that they receive. This process is repeated for each transmitting antenna, and the resulting responses are recorded in \(s(x_t, y_t, x_r, y_r, \omega)\), where \((x_t, y_t, Z_0)\) is the position of the transmitting antenna and \((x_r, y_r, Z_0)\) is the position of the receiving antenna.

If the scene contains a single point reflector at position \((x, y, z)\) with reflectivity \(f(x, y, z)\), the signal recorded back at the receiving antennas will be, ignoring amplitude effects:

\[
s(x_t, y_t, x_r, y_r, \omega) = f(x, y, z) e^{-j k \sqrt{(x-x_t)^2 + (y-y_t)^2 + (z-Z_0)^2}} \times e^{-j k x (x-x_r)^2 + (y-y_r)^2 + (z-Z_0)^2} \tag{13}
\]
where the first exponential term represents the phase delay from the transmitter to the point reflector, and the second term represents the delay back to the receiving antenna. To get the response for the entire scene, integrate over all space:

\[
s(x_t, y_t, x_r, y_r, \omega) = \iiint_{\text{scene}} f(x, y, z) \\
\times e^{-jk\sqrt{(x-x_t)^2+(y-y_t)^2+(z-z_0)^2}} \\
\times e^{-jk\sqrt{(x-x_r)^2+(y-y_r)^2+(z-z_0)^2}} \, dx \, dy \, dz
\] (12)

Again, the exponential terms can be expressed as sums of plane waves:

\[
s(x_t, y_t, x_r, y_r, \omega) = \iiint_{\text{scene}} f(x, y, z) \\
\times \iiint e^{-j(k_x(x-x_t)+k_y(y-y_t)+k_z(z-z_0))} \, dk_x \, dk_y \, dk_z \\
\times \iiint e^{-j(k_x(x-x_r)+k_y(y-y_r)+k_z(z-z_0))} \, dk_x \, dk_y \, dx \, dy \, dt
\] (13)

Rearranging the integrals, we obtain:

\[
s(x_t, y_t, x_r, y_r, \omega) = \iiint_{\text{scene}} \left( \iiint f(x, y, z) \exp\left(j\left(k_x(x-x_t)+k_y(y-y_t)+k_z(z-z_0)\right)ight) \, dx \, dy \, dz \right) \\
\times \exp\left(j\left(k_x(x-x_r)+k_y(y-y_r)+k_z(z-z_0)\right)\right) \, dk_x \, dk_y \, dk_z
\] (14)

\[s(x_t, y_t, x_r, y_r, \omega) = \iiint_{\text{scene}} f(x, y, z) \exp\left(j(k_x x + k_y y + k_z z - k_0 z_0)\right) \, dx \, dy \, dz\] (15)

where the inner 4D Fourier transform is from \((x_t, y_t, x_r, y_r)\) to \((k_x, k_y, k_z, k_0)\) and the outer inverse 3D Fourier transform is with respect to \((k_x, k_y, k_z)\). The Stolt transform \(\Phi(\cdot)\) is therefore used to map from \((k_x, k_y, k_z, \omega)\) space to \((k_x, k_y, k_z)\) space, according to:

\[
k_x = k_{x_t} + k_{x_r}
\]
\[
k_y = k_{y_t} + k_{y_r}
\]
\[
k_z = k_{z_t} + k_{z_r} = \sqrt{\frac{\omega^2}{c^2} - k_{x_t}^2 - k_{y_t}^2} + \sqrt{\frac{\omega^2}{c^2} - k_{x_r}^2 - k_{y_r}^2}
\] (17)

C. Single-transmitter Range Migration

The final variant of the RMA algorithm works with just one transmitter while all other antennas are receivers. By combining Callow et al.’s [13] single-transmitter algorithm for 2D radar imaging with Equation 16, we can derive an expression for the single-transmitter case. In this approach, we merely set \(x_t = y_t = k_{x_t} = k_{y_t} = 0\), as there is only one transmitter located at the center of the array, simplifying to:

\[
f(x, y, z) = FT_{3D}^{-1} \{ \Phi \{ FT_{2D} \{ s(x_t, y_t, \omega) \} \} e^{-jk_z Z_0} \}
\] (18)

III. A NEW IMAGING ALGORITHM FOR MOVING OBJECTS

Objects that move during imaging will cause both blurring and a frequency (Doppler) shift in the reflected wave. If this Doppler shift is measured, the velocity of the moving object can be calculated. A novel algorithm is therefore presented where the Doppler shift measurement is incorporated into the RMA algorithm to create both a velocity map of objects in the scene and a deblurred reflectivity image. This algorithm has great application in gesture imaging systems.

The algorithm works by collecting samples over a period of time at the receiving antenna, rather than just taking a single measurement. The signal at receive antenna can therefore be represented, after downconversion, as:

\[
s(x_a, y_a, \omega, t) = \iiint_{\text{scene}} f(x, y, z) e^{i\psi(x, y, z)t} e^{-2jkR} \, dx \, dy \, dz
\] (19)

where \(R = \sqrt{(x - x_0)^2 + (y - y_0)^2 + (z - Z_0)^2}\) and \(\psi(x, y, z)\) is the Doppler shift caused by the motion of the object at position \((x, y, z)\). Taking the Fourier transform with respect to time gives:

\[
s(x_a, y_a, \omega, \omega_d) = \iiint_{\text{scene}} f(x, y, z) \delta(\omega_d - \psi(x, y, z)) e^{-2jkR} \, dx \, dy \, dz
\] (20)

The Doppler shift, \(\psi(x, y, z)\), caused by a moving object at position \((x, y, z)\), is related to its velocity \(m(x, y, z)\) by

\[
\psi(x, y, z) = \frac{2m(x, y, z)\omega}{c}
\] (21)

The effect of the carrier frequency, \(\omega\), on the Doppler shift is removed by interpolating from \(\omega_d\)-space (Hz) to \(v\)-space (velocity, m/s) according to \(v = \frac{\omega_d c}{2}\).

\[s(x_a, y_a, \omega, v) = \iiint_{\text{scene}} f(x, y, z) \delta(v - m(x, y, z)) e^{-2jkR} \, dx \, dy \, dz
\] (22)

By holding \(v\) constant in Equation 22, we get the response of all the objects in the scene moving at a given velocity. We therefore regard \(s(x_a, y_a, \omega, v)\) as a set of 3D matrices \(s_1(x_a, y_a, \omega)\), each representing the response of the scene at velocity \(v_1\). The standard RMA algorithm (such as Equation 7) is run on each \(s_1\), giving a set \(f_i(x, y, z)\) images. The final reflectivity image of the scene is given by:

\[f'(x, y, z) = \max_i f_i(x, y, z)\] , computed for each voxel.

The final velocity map \(m'\) is

\[m'(x, y, z) = v_j(x, y, z)\] where \(j(x, y, z) = \arg \max_i f_i(x, y, z)\) (24)
again computed for each voxel. The limitation that this algorithm can only measure the velocity component perpendicular to the antenna array can be overcome by using multiple arrays.

IV. THE CHARACTERIZATION TESTBED

There has been no known attempt to experimentally compare and characterize the performance of these near-field microwave imaging algorithms using the same testbed. A single transmit antenna and a single receive antenna were therefore mounted on a XY table, as shown in Figure 1, such that the two antennas can be moved around independently on the XY-plane. This allows any 2D antenna array configuration to be emulated.

The objects to be imaged are placed beneath the antennas. To enable the imaging of moving objects, a linear actuator is also mounted vertically beneath the antennas, so that objects can be moved in a repeatable way during imaging. The XY table and antenna configuration is illustrated in Figure 2.

Figure 3 shows the RF transceiver circuit used in the experimental testbed. With the exception of the signal generator, all other components are off-the-shelf parts that can easily be integrated onto a PCB or inside a custom chip. Three different types of antennas, as pictured in Figure 4, were evaluated to determine their effect on image quality. The horn is the only commercial antenna; the patch and Vivaldi antennas are simple PCB antennas that can be fabricated at extremely low cost.

For the experiments, the RF transmit power, the antenna positions and the target object configuration were varied. Standardized resolution phantoms were created and used to measure the image resolution and image signal-to-noise (SNR) ratio in each case. Figure 5 shows a brass phantom, consisting of metallic strips arranged at decreasing intervals that was used for many experiments. A similar phantom was also created using strips of pig skin to emulate human tissue. Finally, a human hand phantom, shown in Figure 5, was created using pig skin, muscle and fat to verify the usefulness of microwave imaging systems for gesture recognition.

For each experiment, resolution was measured using the resolution phantoms and the 50% amplitude (or full-width half-maximum) criterion. Image SNR was calculated according to the industry standard metric $SNR_{image} = \frac{\mu_{object} - \mu_{bg}}{\sigma_{bg}}$, where $bg$ is the background.

V. CHARACTERIZATION RESULTS

For the results shown here, an 80x80 antenna array with 5mm antenna spacing was emulated, with the RF signal sweeping from 17-20GHz and the metal resolution phantom placed 0.5m below the antenna array, unless specified otherwise.
Figure 6 shows typical 3D images that these algorithms are able to produce, for both stationary and moving objects.

Fig. 6. Typical 3D microwave images generated using the testbed. Left: a 3D projection of three aluminum balls, 40mm in diameter, placed 400mm apart in an equilateral triangle arrangement. The three balls were suspended 0.5m, 0.65m and 0.8m below the antenna array. Top right: Top view of the three balls. Bottom right: A 3D doppler image of a rectangular metal plate, moving up at 45mm/s, and a smaller aluminum ball, moving up at 20mm/s.

Figures 7 and 8 show the effect of varying the RF transmit power. With an image SNR of 10 being the lowest usable image quality, it was found that all three imaging algorithms produced good images at a transmit power of -30 dBm or higher. Increasing transmit power causes a correlated increase in image SNR, until saturation. The single-transmitter algorithm produced the highest image SNR for a given transmit power, due to the imaged object always lying within the main gain lobe of the centrally-located transmit antenna. The Doppler and colocated algorithms produced similar image SNR results, with the Doppler algorithm performing slightly better due to the additional time samples collected.

![Image](image1.png)

It was found that transmit power had little influence on image resolution, provided that the minimum image SNR was met. Both the colocated and Doppler algorithms delivered an average resolution of 12.5mm over the power range, closely matching the 10mm theoretical resolution [6]. The single transmitter algorithm provides a resolution of 20mm, as expected due to a smaller effective aperture of having only one transmitter. The MIMO algorithm was tested with a small number of transmitting antennas and performed identically to the single-transmitter algorithm; hence, its curve is not shown.

The quality of the images is most influenced by the size of the planar array (i.e. number of antennas per side), as shown in Figure 9, where a transmit power of 6 dBm was used. At small array sizes, the resolution is directly proportional to the array size. At larger arrays, the resolution becomes limited by the wavelength. Increasing the array size results in a nearly proportional increase in image SNR.

![Image](image2.png)

Fig. 9. Effect of antenna array size on image resolution and SNR

While uniform antenna arrays are conventionally built with antennas half a wavelength ($\frac{\lambda}{2}$) or less apart, Figure 10 shows antennas can be placed up to 0.9$\lambda$ apart without much loss of resolution or image SNR, and only very minor aliasing. On the other hand, placing antennas $\frac{\lambda}{2}$ apart results in approximately a 33% increase in image SNR when compared to $\frac{\lambda}{2}$ spacing.

![Image](image3.png)

Fig. 10. Effect of antenna spacing on image quality when aperture is fixed
TABLE I
COMPARISON OF DIFFERENT ANTENNAS FOR IMAGING

<table>
<thead>
<tr>
<th>Antenna</th>
<th>Norm. Resolution</th>
<th>Norm. Image SNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horn</td>
<td>10mm</td>
<td>1</td>
</tr>
<tr>
<td>Patch</td>
<td>15mm</td>
<td>0.94</td>
</tr>
<tr>
<td>Vivaldi</td>
<td>8mm</td>
<td>0.95</td>
</tr>
</tbody>
</table>

It is well known that the depth resolution of the imaging system is given by $c/2\pi f$, where $B$ is the RF bandwidth [6]. Using the imaging testbed, the RF bandwidth was varied from 500MHz to 3GHz and the resolution and image SNR measured. The depth resolution measured at each bandwidth matched the theoretical value to within 10%. Furthermore, increasing the number of frequency samples with the bandwidth caused an increase in image SNR.

Most of the results presented in this paper were obtained using commercial horn antennas. Since these antennas are relatively expensive and hence not ideal for low-cost imaging arrays, custom PCB antennas, which can be manufactured extremely cheaply in bulk, were therefore designed and fabricated as an alternative. Three antennas, shown in Figure 4, were evaluated and their relative performance is compared in Table I. Since it is the relative performance that is of interest, the results have been normalized to 10mm resolution and an image SNR of 1 for the horn antenna.

There was little variation in image SNR, with the horn being slightly less noisy due to its better $S_{11}$. The patch antenna had poor resolution due to the large phase center errors associated with patches. The Vivaldi antenna, however, produced high resolution images due to its wide bandwidth, making it an excellent candidate for low-cost microwave imaging systems.

To determine the effect of target material, pig-skin phantoms were also imaged. Figure 11 shows that imaging the skin resulted in slightly better image resolution and SNR, when compared with the metallic phantom. This is believed to be due to the fact that the microwaves reflect in a diffuse manner off skin, making the reflected signal easier to capture, while the reflection is specular for metallic objects.

The first two experiments (Figures 7 and 8) where the transmit power was varied, were, in effect, varying the RF SNR at the receive antenna. This effect is studied in more detail in Figure 12, where the effect of RF SNR is determined using a sophisticated software simulation that models external noise, component noise, path loss, reflective losses, and component non-linearities. The simulation shows that the colocated imaging algorithm produces good, high resolution images for an RF SNR of -15 dB or higher. In the linear region, $\text{SNR}_{\text{image}}(\text{dB}) \approx \text{SNR}_{\text{RF}} + 30\text{dB}$, due to array gain less receiver component and algorithm noise.

![Fig. 12. Simulation: Effect of RF SNR on image resolution and image SNR](image-url)

Since clock synchronization can be challenging in large arrays, the effect of clock jitter on image quality was also simulated. It was found that uniformly random clock jitter with a maximum deviation of 20% of the RF clock period resulted in just a 10% decrease in image SNR. A maximum jitter deviation of 40% still produced acceptable images.

The velocity measurements provided by the doppler imaging algorithm were found to be accurate within 5% over a range of typical human velocities (40 to 100mm/s). The Doppler imaging algorithm enables this high level of accuracy by combining measurements from a range of carrier frequencies.

VI. ENERGY AND COST ANALYSIS

The relationship between RF SNR at the receiving antenna and image SNR was illustrated in Figure 12. Since both the transmit power and the noise figure (NF) of the receiver low-noise amplifier (LNA) affect RF SNR, improving either one will improve image SNR. However, increasing transmit power or decreasing LNA noise figure will increase power consumption. This suggests that image SNR can be traded off for power consumption.

This trade-off is very important, as high-resolution imaging systems require large numbers of microwave transceivers, which can result in high power consumption. To make these large arrays viable, power consumption needs to be reduced as much as possible without sacrificing image quality. In fact, transmitting at very high power levels usually offers little advantage over more moderate transmit levels, as the maximum image quality is often limited by ADC quantization noise.

The goal is therefore to operate the imaging system in such a way that the ratio of image quality to energy consumed is maximized. To aid in this goal, a new figure of merit (FOM) is defined for microwave imaging systems:

$$FOM = \frac{\text{SNR}_{\text{image}} \times N_{\text{pixels}}}{E} \left[\text{SNR/\text{Joule/voxel}}\right]$$  \hspace{1cm} (25)$$

This new figure of merit describes how efficiently an imaging system can create a microwave image of a given size and image quality. The metric can also be viewed as the image

![Fig. 11. Effect of target material on image resolution and SNR](image-url)
SNR that the system is able to generate per Joule of energy expended per voxel in the image. The figure of merit does not include resolution, as Figure 12 showed that resolution is not affected by RF SNR and hence power consumption.

As was shown in Section V, image SNR is determined primarily by transmit power, number of antennas, receiver noise and external noise. The energy consumed is determined by the number of transceivers, the power consumption of the transmitter and receiver, and the integration time. Furthermore, both the image SNR and energy consumption are influenced by the choice of imaging algorithm.

It is also clear that the target or scene being imaged will influence the image SNR (see Figure 11, for example), and hence the figure of merit. However, the figure of merit should evaluate the imaging system only, and be independent of the scene. While the figure of merit could be modified to compensate for the effect of the scene (such as including terms for the distance to and radar cross section of each object in the scene), it was instead decided that a "standard scene" would be used when evaluating the figure of merit. The standard scene was chosen to be a metallic sphere, 0.1m in diameter, placed 1m in front of the imaging array.

Since image SNR is a complex, non-linear function of parameters such as transmit power, number of antennas, receiver noise and external noise, a closed-form expression for image SNR cannot be developed. Furthermore, it is difficult to accurately vary external and receiver noise in the real world. Therefore, a MATLAB software simulation was used in place of the imaging testbed to measure image SNR over a range of these parameters. The architecture of the noise model is shown in Figure 13. It models all the transmitters, path losses, reflecting objects in the scene, noise sources and component variation in order to calculate received signal power and received noise. This simulated received signal plus noise is then fed into one of the microwave imaging algorithms for processing. The parameters associated with each component of the noise simulation is shown below the dotted line in Figure 13. Due to the large number of parameters, only the underlined parameters were varied for the simulations, while the others were set to nominal values based on lab measurements.

![Image SNR](image.png)

Fig. 13. The architecture of the noise and energy simulation model

Unlike image SNR, the energy required to form the image can be calculated analytically from the experimental parameters. The power consumed by the transmitter is determined primarily by the power amplifier (PA). Assuming the PA has efficiency \( \eta \), the power required for a single transmission is:

\[
P_{PA} = \eta \cdot P_{TX}
\]

Since passive mixers and low-speed ADCs can be used at the receiver, the LNA dominates the receiver power consumption. As a first order approximation, the noise figure of an LNA is inversely proportional to its bias current squared [14]. Since power consumption is directly proportional to bias current squared, the LNA's power consumption is related to its noise figure via:

\[
P_{LNA} = \frac{\alpha}{N_{FLNA}}
\]

where \( \alpha \) is a device technology parameter. Furthermore, the noise figure of the entire receive chain is determined primarily by the LNA's noise figure, due to its high 50 dB gain. We can therefore assume that the component noise at the receiver can be completely characterized by the LNA noise figure.

Expressions for the total energy required to form an image can therefore be given for both the colocated and single-transmitter RMA algorithms, where \( N_{ant} \) is the number of antennas, \( N_f \) is the number of frequency steps and \( T_{int} \) is the amount of time spent transmitting, receiving and then integrating each frequency step at the receiver. Note that the single-transmitter algorithm clearly uses less energy, as each frequency step is only transmitted once.

\[
E_{coloc} = \left( \eta \cdot P_{TX} + \frac{\alpha}{N_{FLNA}} \right) \cdot N_{ant} \cdot N_f \cdot T_{int}
\]

\[
E_{STX} = \left( \eta \cdot P_{TX} + \frac{\alpha}{N_{FLNA}} \right) \cdot N_f \cdot T_{int}
\]

While this section has mostly discussed minimizing energy consumption for imaging systems, cost is also important. However, cost is difficult to model, as it varies greatly with technological breakthroughs, market trends and volume. However, reducing the number of antennas, using cheaper LNAs with higher noise figures and reducing total power consumption will all help reduce cost. Therefore, it is assumed that energy minimization is a good proxy for cost minimization.

VII. RESULTS OF ENERGY AND COST ANALYSIS

For the energy simulations and calculations, PA efficiency \( \eta \) was set to 0.1 and LNA parameter \( \alpha \) was set to 0.16W so that they matched devices used for the experiments in Section V.

As explained previously, transmit power and LNA noise figure are the parameters that most affect energy consumption. The transmit power was therefore varied from -30 dBm to 6 dBm, and the LNA noise figure from 3 dB to 51 dB, while the figure of merit was computed at each operating point. The power configuration that produced the best figure of merit for five different scenarios is shown in Figure 14. The scenarios included different array sizes, imaging algorithms, distance from array to target sphere and amounts of external interference. The scenarios are labeled as follows:
The 80x80 configuration produced its best figure of merit with -12 dBm transmit power and a LNA noise figure of 24 dB. While the noise figure may seem high, the noise generated by the different LNAs is uncorrelated and adds incoherently. Therefore, after processing, the SNR improves by a factor proportional to the number of antennas [15]. At the optimum operating point, each transmit PA consumes -2 dBm power and each LNA consumes -2 dBm. It is not coincidence that the best figure of merit is obtained when the transmitter and receiver consume equal power. It is well known that the most power efficient way to achieve a certain link margin in low-power wireless systems is to distribute the power evenly between the transmitter and receiver [16].

When external interference is added (80x80 interf.), the transmit power increases and the LNA noise figure decreases to maintain the same RF SNR at the receiver, while evenly distributing the power consumption between PA and LNA.

If the distance between the antenna array and target sphere is halved (80x80 0.5m), the combined path loss decreases by 12 dB. With the extra 12 dB margin, the simulation shows the transmit power decreasing by 6 dB and the LNA noise figure increasing by 6 dB, as expected. This result highlights the importance of using a standard scene when evaluating the figure of merit, as the distance to target has a large effect.

If the array is increased in size to 160x160 antennas, the 4X increase in the number of antennas gives an extra 6 dB array gain. The results show that this allowed the transmit power to decrease by 3 dB and the LNA noise figure to increase by 3 dB, resulting in 3 dB less power consumption overall.

The last simulated scenario was the single transmitter algorithm (80x80ST). The transmitter transmits once only, and this signal is shared by all the receivers. The most energy efficient approach is therefore to increase the transmit power and to decrease the power consumption at receivers, such that the power consumption of the single transmitter is equal to the combined power consumed by all the receivers. Consequently, the transmitter consumes $N^2$ more power than each receiver, for an NxN array. This is illustrated by the 3 dBm transmit power and the 45 dB noise figure for the LNAs.

It should be mentioned that in some scenarios the optimum figure of merit was obtained by setting the image SNR so low that the images became useless. Therefore, the image SNR was restricted to 10 or higher during the search process.

Figure 15 shows the energy required to compute a single voxel for each scenario, when operating at the best figure of merit. Halving the distance to the target results in 4x less energy consumption. The addition of external interference requires 25% more energy. The 160x160 array interestingly requires only half as much energy to compute a voxel as the 80x80 array. This is because the PA and LNA both operate at half the power, and even though there are more transceivers, the energy consumption is normalized per voxel. In theory, the single transmitter should consume N=80 times less energy than the colocated algorithm, but the simulations showed a 160x reduction due to the simulation step size.

Finally, Figure 16 shows how the figures of merit compare for the different scenarios. Even though the single transmitter algorithm produces lower resolution images, it is much more energy efficient, as the single transmitter simultaneously transmits to all the receivers. Furthermore, larger arrays have higher figures of merit than smaller arrays. Specifically, the figure of merit is proportional to the number of antennas per side of the array. Lastly, external interference and longer distances between array and scene can degrade the figure of merit.

**VIII. DESIGN PROCEDURE FOR ENERGY EFFICIENCY**

The results shown here suggest a methodology for designing energy-efficient antenna array systems for microwave imaging. The required image resolution directly specifies the array
aperture, as characterized in Figure 9. Furthermore, large arrays are more energy efficient, as shown in Figure 16.

Next, the minimum required image SNR should be determined based on the desired application. Decreasing the required image SNR to this level permits a lower RF SNR, and in turn a lower transmit power and a higher noise figure for the LNAs (see Figures 7 and 12). Using Figure 12, the RF SNR required to meet this image SNR can be determined. The transmit power and LNA noise figure can then be calculated to achieve this RF SNR, while ensuring that the transmitter and receiver consume equal power. This second requirement is essential for ensuring energy efficiency. The calculation can be performed using standard path loss and radar cross-section formulas. If significant RF interference is expected, the transmit power can be increased slightly and the noise figure decreased slightly to accommodate the interference.

To further reduce cost, the antennas can be placed more than $\frac{1}{2}$ apart without significant image quality loss, reducing the number of required transceivers. PCB antennas, such as Vivaldi antennas, can be used in place of horn antennas, as they are significantly cheaper and work just as well.

IX. CONCLUSION

The four near-field microwave imaging algorithms that were compared, namely the colocated, MIMO, single-transmitter and Doppler RMA algorithms, were all found to produce good quality images at low transmit power and SNR levels. This result suggests that these algorithms can be used to build imaging arrays that are affordable due to the use of relatively noisy components and have low power consumption. Furthermore, the relationships between image quality and array size/configuration have been explored, enabling the system designer to effectively trade-off performance with cost.

A novel figure of merit was introduced for determining how efficiently these systems can compute a single voxel. The colocated RMA algorithm achieved the best figure of merit when the transmitter and receiver consumed equal energy, while the single transmitter algorithm preferred a high power transmitter and a low power receiver. It was found that the figure of merit could be improved by increasing the array size or changing from the colocated to single transmitter algorithm.

It has also been verified that these algorithms work well when imaging human hands, validating their use in gesture-recognition systems, especially when paired with the Doppler imaging algorithm.

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REFERENCES


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