Identifying Acoustic Wave Sources on the Sun. I. Two-dimensional Waves in a Simulated Photosphere

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Abstract

The solar acoustic oscillations are likely stochastically excited by convective dynamics in the solar photosphere, though few direct observations of individual source events have been made and their detailed characteristics are still unknown. Wave source identification requires measurements that can reliably discriminate the local wave signal from the background convective motions and resonant modal power. This is quite challenging as these noise contributions have amplitudes several orders of magnitude greater than the sources and the propagating wave fields they induce. In this paper, we employ a high-temporal-frequency filter to identify sites of acoustic emission in a radiative magneto-hydrodynamic simulation. The properties of the filter were determined from a convolutional neural network trained to identify the two-dimensional acoustic Green’s function response of the atmosphere, but once defined, it can be directly applied to an image time series to extract the signal of local wave excitation, bypassing the need for the original neural network. Using the filter developed, we have uncovered previously unknown properties of the acoustic emission process. In the simulation, acoustic events are found to be clustered at mesogranular scales, with peak emission quite deep, about 500 km below the photosphere, and sites of very strong emission can result from the interaction of two supersonic downflows that merge at that depth. We suggest that the method developed, when applied to high-resolution high-cadence observations, such as those forthcoming with the Daniel K. Inouye Solar Telescope, will have important applications in chromospheric wave studies and may lead to new investigations in high-resolution local helioseismology.

Unified Astronomy Thesaurus concepts: The Sun (1693); Solar physics (1476); Solar photosphere (1518); Helioseismology (709); Solar granulation (1498); Solar oscillations (1515)

1. Introduction

The Sun and many stars are pulsationally stable but display acoustic oscillations nonetheless. These stars are likely stochastically excited by small-scale convective dynamics, but the detailed properties of the acoustic sources are unknown. Theoretical models differ, and observations are yet unable to differentiate between them.

Understanding the sources of the solar acoustic oscillations is important in assessing their contributions to observed oscillation spectra and consequently in using those spectra to determine stellar properties. Global p-mode line shapes, and thus accurate frequency determinations (e.g., Duvall et al. 1993; Toutain et al. 1998; Benomar et al. 2018, and references therein), depend critically on the depth and properties of the wave sources (Gabriel 1992, 1993; Roxburgh & Vorontsov 1995; Abrams & Kumar 1996; Rast & Bogdan 1998; Philidet et al. 2020b). Moreover, direct contributions of the excitation events to the observations introduces a correlated noise component to the p-mode spectra (Roxburgh & Vorontsov 1997; Nigam et al. 1998), which can reverse the line asymmetries (Duvall et al. 1993) and be used to determine the phase relationship between intensity and velocity fluctuations during excitation events (Skartlien & Rast 2000; Severino et al. 2001; Jeffries et al. 2003, though see Philidet et al. 2020a). Local helioseismological deductions are similarly sensitive to the phase relationship between the waves and their source. For example, the travel-time kernels used in time-distance helioseismology depend on the assumptions about the source characteristics (Gizon & Birch 2002; Birch et al. 2004), and source properties may be particularly critical in the interpretation of multihit local helioseismological measurements if individual sources are spatially and temporally extended or distributed over a range of heights, both of which they are likely to be.

Stochastic excitation by turbulent convection can result from several processes. Approximately monopolar, dipolar, and quadrupolar emission results from fluid compression (volumetric changes), buoyant acceleration in a stratified medium (external stresses), and the divergence of the fluctuating Reynolds stresses (internal stresses), respectively (e.g., Goldreich & Kumar 1990; Rast 1999). Early studies focused on quadrupolar excitation by turbulent motions, the Lighthill mechanism (Lighthill 1952, 1954; Stein 1967; Goldreich & Keeley 1977; Goldreich & Kumar 1990; Balmanforth 1992), which scales as a high power of the turbulent flow Mach number. This mechanism may be most readily observed on the Sun within intergranular lanes in the deep photosphere, as it is there that the flow is most turbulent, with the granular flow otherwise highly laminarized by the steep photospheric stratification (e.g., Nordlund et al. 1997). There is some modeling (e.g., Skartlien et al. 2000; Lindsey & Rempel 2020) and some observational (Rimmele et al. 1995; Goode et al. 1998; Strous et al. 2000; Lindsey & Donea 2013) evidence that solar acoustic excitation preferentially occurs in granular downflow lanes.

The importance of monopolar and dipolar emission due to rapid local cooling (radiatively induced entropy fluctuations) and consequent buoyant acceleration of the fluid in the solar photosphere is also recognized (Stein & Nordlund 1991; Goldreich et al. 1994; Rast 1997; Nordlund & Stein 1998;
Rast 1999; Samadi & Goupil 2001; Samadi et al. 2001), and the particular importance of granular fragmentation and the formation of new convective downdrafts in the solar photosphere has been emphasized (Rast et al. 1993; Rast 1995). Direct observation of wave emission during granule fragmentation has been reported (Roth et al. 2010; Bello González et al. 2010), and helioseismic phase difference spectra show a velocity/intensity phase relation consistent with downflow plume formation (Straus et al. 1999; Skartlien & Rast 2000; Severino et al. 2001). Finally, solar flares have been implicated as strong acoustic sources (e.g., Kosovichev & Zharkova 1998; Ambastha et al. 2003; Donea & Lindsey 2005), though their coupling and energetic importance to solar p-modes is only partially understood (Lindsey et al. 2014). Recent works suggests that flare acoustic sources might be located quite deep in the active region photosphere (Martínez et al. 2020; Lindsey et al. 2020), reanimating that question.

It is likely that acoustic excitation on the Sun leverages one or more of these physical mechanisms, but the precise nature of the excitation events, their phasing with efficiency in coupling to the global modes, and thus their relative importance to excitation, has not yet been quantitatively determined. Routine identification of individual acoustic sources that link the observed local wave field directly to a specific source site would advance this cause. Additionally, detailed characterization of resolved sources could provide a basis for wave mode conversion studies and high-resolution local helioseismology employing the local wave field generated.

The difficulties faced in resolving solar acoustic sources stem from the inherent challenges in separating the faint (three or more orders of magnitudes weaker than the background) local wave field induced by the acoustic events from the background superposition of granular motion and global resonant p-modes. Simulations suffer a similar difficulty; the unambiguous separation of compressible convective motions from the contributions of individual wave sources to the total flow remains problematic. While projection of a simulation solution onto resonant oscillation modes is readily achieved (e.g., Bogdan et al. 1993), identification of the local wave response is difficult. One can formally define the local wave field as distinct from the compressible convection, and thereby identify possible source mechanisms and how they depend on the nonwave flow (e.g., Rast 1999), but unambiguous separation of these wave and nonwave components is in general not possible because the radiated wave field is not viewed in a turbulence-free and source-free region (see, for example, Lighthill’s discussion of sound versus pseudo-sound, Lighthill 1962).

Moreover, the very qualities that make the Sun an excellent resonant cavity also make it difficult to distinguish any individual local source. Inevitably an episode of wave emission from a local source is a small component of the signal compared with the resonant accumulation of acoustic waves, and acoustic wave filters (e.g., Title et al. 1989) act to also reduce the local source signature. Since the spectral content of the low-amplitude acoustic source signal overlaps that of the acoustic modes, and in part also that of the granular motion, linear filtering, and frequency domain noise reduction techniques most often fail in source detection. Some success has been achieved via helioseismic holography, when the analysis is conducted using only high frequency waves, waves that are damped on timescale short compared to their resonant time (e.g., Lindsey & Donea 2013). Using waves above 5.5 mHz these authors identified a statistical bias toward enhanced emission near the edges of granules. A novel approach has recently been proposed for the identification of individual acoustic sources in numerical simulations, the differencing of perturbed and unperturbed solutions, with tantalizing first results (Lindsey & Rempel 2020), but it still remains to be seen how that technique can be carried over to observations.

Here, we report on a robust new method for the unambiguous identification of individual acoustic sources that can be readily applied to observations. The method was developed by, first training a deep-learning algorithm to reliably identify the signature of local acoustic sources in two-dimensional Doppler velocity maps of the photosphere in a MPS/University of Chicago Radiative MHD (MURaM; Vögler et al. 2005; Rempel et al. 2009; Rempel 2014) magnetohydrodynamic simulation of the upper solar convection zone, and then deciphering what underlies the algorithms success. Once diagnosed, we mimicked the filter that the learning algorithm was applying and applied it directly to the simulated photospheric time series (and time series of Doppler maps at other depths), bypassing the dependence on deep learning and allowing direct visualization of the local wave pulses that propagate outward from acoustic source sites. To be effective, the acoustic source filter requires high-cadence (<3 s) and high-spatial-resolution (<50 km) time series. Fortuitously, the observational capabilities required for application to real solar data are just now becoming available with the commissioning of the National Science Foundation’s Daniel K. Inouye Solar Telescope (DKIST).

2. Building the Acoustic Source Filter

2.1. Convolutional Neural Network

Neural networks are a class of algorithms that perform inference without using explicit instructions, relying on patterns and examples instead. They utilize computational statistics, in which algorithms build models based on nonlinear and nonparametric regression over sample data, known as training data, in order to make forecasts or decisions. If the training data are sufficiently broad to capture the relevant correlations, the network can then be used to make inferences within a domain of interest. For our problem, we considered a network architecture inspired by the organization of the visual cortex, known as a convolutional neural network (e.g., Lecun et al. 2015, and references therein). In comparison to a fully connected neural network, this architecture displays superior performance in fitting and classifying data sets of image time series. Successive convolution allows the network to more reliably construct each layer of representation while utilizing a smaller number of parameters. This advantage is fully realized when dedicated graphical processing units (GPUs) are employed because, while they are more limited in local memory, these multi-stream processors allow for fast parallel processing, reducing the time required to train networks and thus allowing training over extremely large data sets.

We have constructed such a convolutional neural network tailored to the identification of local sources of acoustic waves in the photosphere of a MURaM simulation. We have been successful in identifying sources in time series of the evolving Doppler velocity on the two-dimensional photospheric ($\tau = 1$)
plane, pressure perturbations on the same surface, and the evolving continuum intensity. The neural network in all cases is able to capture the spatial and temporal dependencies in the image sequences that define an acoustic source event through the application of multiple convolutional filters. In this paper we focus, for simplicity, on source identification using the photospheric Doppler velocity time series, though the steps taken and conclusions drawn are common to all variables. Details of the network architecture and the training parameters are discussed in Appendix A. Here, we summarize the simulation and training scheme employed.

The physical dimensions of the MURaM simulation employed are \( L_x \times L_y \times L_z = 6.144 \times 6.144 \times 4.096 \text{ Mm}^3 \), where \( L_z \) is the vertical dimension, with gridding for uniform 16 km resolution in all directions. The simulation extends for 1 hour of solar time with a time step of 2.0625 s (1800 frames in total). The data cube thus has the native shape 1800 \( \times \) 384 \( \times \) 384 \( \times \) 256. The top boundary of the simulation is located 1.7 Mm above the mean \( \tau = 1 \) level; the depth of the convecting portion of the layer is 2.3 Mm. Horizontally periodic boundary conditions were employed during the simulation, along with a semitransparent layer is 2.3 Mm. Horizontally periodic boundary conditions were used as source-free examples for the convolutional neural network, while the other half additionally contains acoustic pulses following the Green’s function template above. The acoustic pulses are added to the source-free time series at random positions in space and time, have an amplitude specified by a signal-to-noise ratio \( S/N \), the ratio between the peak velocity of the acoustic response and the peak velocity of the granular flow field within the 80 \( \times \) 80 pixel response template region centered on the local site of interest), and propagate at 8 km s\(^{-1} \), approximately the mean sound speed in the simulation photosphere (\( \tau = 1 \)).

The MURaM photospheric time series can be thought of as being composed of three intrinsic components: convective motions, resonant modulated oscillations, and the wave field produced by local sources, some portion of which couple to the resonant modes. In order to train the neural network to identify local wave sources two things are needed: a template of the expected source signature and a source-free time series of the granulation. In training, the granulation time series can either contain the modal oscillation component or not, but, as discussed in the Appendix B, we construct the training set from the three components separately.

We prepare a \( N_x \times N_y \times N_t = 40 \times 80 \times 80 \) local source response template using the Green’s function solution of the propagating wave in two dimensions,

\[
G(x, y, t; x', y', t') = \frac{c_s}{2\pi \sqrt{t'^2 - x'^2 + y'^2}} \frac{H(t - \frac{\sqrt{x'^2 + y'^2}}{c_s})}{c_s}, \tag{1}
\]

where \( H \) is the Heaviside step function, \( c_s \) is the speed of sound (taken in the two-dimensional approximation to be the mean value at the depth being analyzed), and \( x, y, \) and \( t \) on the right-hand side are measured relative to the impulse location and time (equal to \( x - x', y - y', \) and \( t - t' \), respectively). We note that this is not the true Green’s function of the three-dimensional stratified atmosphere (e.g., Rast & Bogdan 1998), but approximates it in the plane of the source height. We anticipate employing the true Green’s function when identifying sources in real data, as that will allow simultaneous extraction of the source height and position, but we use the simplified Green’s function here to illustrate the analysis techniques we have developed. With Equation (1) the source response template can be readily constructed as

\[
\phi(x, y, t) = \int_V G(x, y, t; x', y', t') S(x', y', t') \, dx' \, dy' \, dt'.
\]

(2)

Taking \( S(x', y', t') \) to be a narrow Gaussian in space and time (we take \( \sigma_x = 16 \text{ km} \) and \( \sigma_y = 2 \) so that it corresponds to an unresolved \( \delta \)-function at the Nyquist frequency of the spatiotemporal grid), \( \phi(x, y, t) \) serves as the acoustic source-response template.

Since the simulated photosphere itself likely has sites of acoustic emission (not a priori identifiable), the MURaM time series itself cannot be used directly in training the network, as the goal of training is to separate the sources from the other flow components. Instead, using the MURaM photospheric slices, we construct an artificial data set that captures a source-free version of the granulation and its evolution (detailed in Appendix B). Half of these artificial granulation time series are used as source-free examples for the convolutional neural network, while the other half additionally contains acoustic pulses following the Green’s function template above. The acoustic pulses are added to the source-free time series at random positions in space and time, have an amplitude specified by a signal-to-noise ratio \( S/N \), the ratio between the peak velocity of the acoustic response and the peak velocity of the granular flow field within the 80 \( \times \) 80 pixel response template region centered on the local site of interest), and propagate at 8 km s\(^{-1} \), approximately the mean sound speed in the simulation photosphere (\( \tau = 1 \)).

Using these samples, the convolutional neural network is trained to classify a given test sample as containing acoustic emission or not; it is trained to determine whether a source is found at a given place and time or not. Effectively, the training determines both the connectivity between the network layers and the properties of the series of large and small convolutional kernels applied at each layer so that the loss function is minimized for a given source \( S/N \).

To assess the best training strategy, we trained the convolutional neural network multiple times, each time with a fixed acoustic source amplitude. Figure 1 (top) plots the training accuracy for acoustic pulse amplitudes \( S/N \in [-10, -20, -30, -40] \text{ dB} \), when the length of the convolutional kernels in time \( n_t \) as detailed in Appendix A) are varied until maximum accuracy is obtained for each source \( S/N \). Accuracy is defined as one minus the mean-absolute error, the mean value over a thousand test samples (not used during training) of the source probability as returned by the network after training minus the artificial source ground truth. It is computed over both source-free time series and time series with sources, so that both false positive and false negative detections are accounted for. When the source \( S/N \) equals 0 dB (i.e., the ratio of the maximum amplitude of the acoustic response to the local granular flow is 1 in the training set), the local wave signal is clearly apparent in individual images (Figure 2), the loss function of the network converges to a minimum even for \( n_t = 3 \), and the network can reliably classify the existence of the acoustic emission with an accuracy of 99.5\% for an \( S/N \) of −10 dB, the loss function of the network still converges with \( n_t = 3 \), but the network exhibits a reduced accuracy of 95\%. The accuracy further drops as the \( S/N \) of the training source is
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a

b

Figure 1. In (a), source identification accuracy during network training, one minus the mean-absolute error over 1000 test samples (not used in training, but constructed with the same source strength as the training set) as a function of the source strength (acoustic pulse S/N in decibels (dB)). In (b), measured rates of false detection after training with −20 dB sources. Plots separately for false positives (blue/top) and false negatives (red/bottom).

decreased to −20 dB. For these weak sources, most of the prominent signatures of the acoustic emission in individual image frames is lost in the granular flow (Figure 2) and learning convergence is difficult to achieve, requiring longer duration convolutional kernels (n_t > 4) and multiple training initiations for successful minimization of the loss function.

The increase in n_t required for learning convergence, which accompanies the decrease in source strength, suggests that at low S/N, convergence requires a noise-specific denoising filtering that is not accessible in shorter time series but that can be reliably leveraged to allow source identification with longer convolutional kernels. In other words, as the source strength decreases, the network leverages, via longer duration convolutional kernels, the difference between the temporal evolution of the granulation (the noise) and that of the local wave (its propagation at the sound speed) to identify the source site. But there is a limit to the source amplitude below which this strategy no longer works: training accuracy drops to 50% (no better than random chance) for a source S/N lower than about −40 dB, even when the convolutional kernel includes many time steps (n_t ≥ 10). Since the amplitude of the wave pulse drops with time as it expands, it no longer contributes significantly at these longer times to the characteristic spatiotemporal signature underlying the neural network identification strategy.

Based on this analysis, we trained the final neural network with artificial time series in which granulation and sources have a fixed S/N of −20 dB. We prepared 5000 training time series, half with the acoustic pulses randomly located somewhere in space and time, and the other half with no pulse. With these, an ensemble of neural networks, each with different initiation parameters, was trained, and the network with the highest accuracy on the test samples was used in the analysis of the original MURaM data (detailed results in Section 3).

In that analysis, the application of the network to nontraining data returns a confidence value at every location in the each image at each time in the time series. This is effectively a measure of the cross correlation between the image time series and the Green’s function response kernel, but is not a direct measure of that correlation. As discussed above, the neural network simultaneously applies a denoising scheme that allows it to recover the spatiotemporal structure of sources underlying the granulation that cannot be easily uncovered otherwise. Figure 3 (top) indicates all the locations in a single time step of the MURaM time series at which the neural network returned a confidence value greater than 84% (indicating 84% or better confidence that an acoustic source occurred at that location at that time). It is important to note that the network might register multiple source detections as it scans through a single source in space and time. This is because the network can return a confidence value above 84% even if the source is not precisely at the center of the template’s field of view or if it is slightly offset in time. Such assignments can lead to multiple false detections, as there can be cases in which the confidence of the network at the site of acoustic emission is nearly 100%, while the confidence of the nearby pixels (in both space and time) remains above 84%. The network has finite resolution. From our analysis, we find that a site of strong acoustic emission can cause an expanded detection region with a spread of about ±6 pixels in space and ±4 pixels in time away from the center of its actual spatiotemporal location (hence positive detection by the network is shown by green circles in Figure 3). The clusters in the field of view of Figure 3 (top) contain several sources, densely packed together, each contributing multiple detections. This is evident in Figure 3 (bottom), as discussed in the next section.

We note that even though the network was trained for sources with a fixed S/N of −20 dB, it is able to uncover sources with a range of strengths, depending on their location and phasing with respect to the background granular flow. This is illustrated by Figure 1 (bottom), which plots the fraction of false positives and false negatives (compared to total number samples tested) returned as a function of source strength, when the −20 dB S/N trained neural network is applied to a set of time series created by embedding 1000 artificial sources of a given strength at random positions and times in artificial source-free granulation time series. The network is able to identify 69% of sources of strength −30 dB with a false positive rate of 19% and false negative rate of 12%.

2.2. Learning-algorithm-derived Acoustic Source Filter

Despite the success of the deep-learning algorithm that we have developed, the algorithm itself remains characteristically opaque. It is difficult to determine why the network is performing an operation or how it relates to the optimal solution for the problem. This characteristic opacity is the heart of the black box problem, a problem with significant practical and theoretical consequences. Practically, it is difficult to trust, optimize, and systematically improve an algorithm whose
workings are not transparent. Theoretically, the black box problem makes it difficult to evaluate the mathematical rigor of the solution and its domain of reliability. Additionally, the algorithm only returns the probability that a particular site location is a source. Alone, this offers limited physical insight. To overcome these difficulties, we have unwound the complicated, interlaced convolutional kernels our deep-learning algorithm defined, and have deconstructed them into a set of linearly summed traditional operators, converting the black box to a glass box. Details are provided in the appendices. Here, we summarize the most salient results.

As described in the previous section, when the source S/N is 0 dB, the spatiotemporal structure of the acoustic emission is prominent in image time series and the convolutional filter by default concentrates on capturing those geometric patterns in order to identify a source occurrence. However, as the S/N drops below −10 dB, these features are lost in the background (the granular flow field) and the network requires application of a denoising filter to discern the source. From our examination of the neural network behavior in the previous section, it is evident that this denoising is accomplished by increasing the temporal length of the convolutional kernel. This suggests that the denoising is taking place along the temporal axis of the data as the signal gets weaker, and based on this understanding, we designed a reduced network aimed at separating the denoising kernel from the spatiotemporal source kernel. Its architecture is sketched in Figure 4. The network begins with a large nonlearnable kernel, the Green’s function solution for the propagating wave \(\phi\) as given by Equation (2), which is convolved with the input Doppler map. This layer serves to capture the spatiotemporal features of the source for the network. The next layer consists of a \(6 \times 1 \times 1\) trainable convolutional kernel whose sole purpose is to capture the denoising scheme essential to the network’s success. These two convolutional layers are followed by a max-pooling layer, which encodes all the information produced by the convolutional filters in a lower-dimensional feature space. This encoded cube is flattened and used by the network to make the decision for identification.

An ensemble of networks with this architecture were trained, using sources having −20 dB S/N as before. We examine the trained temporal denoising kernels achieved and found that they converge to a simple form: \((0.1, -0.5, 1.0, -1.0, 0.5, -0.1)\) (normalized). This is an oscillatory function, a custom high frequency filter in time, somewhat resembling a Morlet wavelet or a sinc function, but performing better in tests than either of those. More explicitly, the kernel is the weighted difference of six successive planes along the temporal axis of the convolved data cube. It serves to cancel the background flow, leaving only tiny fluctuations that preserve the residual convolved source response riding on a nearly constant background. In addition, isolated pixels have very large values, likely caused by granular edges, which can dominate the color table when displaying the images. To remove these we clip all the large values from the filtered residual time series, restricting the residual map to values between \([-0.001, 0.001]\). Examples of the results are displayed in Figures 3, 5, and 6. Since variations in this residual convolution map do not indicate true upflow and downflows, we plot only its magnitude.

What is notable is that acoustic sources, and the resulting local propagating wave field they induce, can be directly visualized in Doppler map time series by applying the following neural network motivated operations, in order:

1. Convolve the Doppler map time series with a template of the Green’s function solution for the propagating wave \(\phi\).
2. Convolve the resulting data cube with the temporal kernel \((0.1, -0.5, 1.0, -1.0, 0.5, -0.1)\), or equivalently, apply a weighted difference filter over six successive frames along the temporal axis of the convolved data cube.
3. Clip large values from the filtered time series by restricting the residual map to values between $[-0.001, 0.001]$.

4. Take the absolute value of the residual map.

This procedure can be compared with a carefully defined Fourier filter in $k - \omega$ space (see Section 4 below). Since it does not depend on the vast set of parameters of the deep-learning solution, parameters that are rooted in training constraints, it can be applied as a robust compact mathematical operator directly to observational data. We are planning to work with early DKIST data to explore that possibility in detail.

3. Results

Extracting acoustic emission signatures by direct application of the image filter described above (Section 2.2) to an image time series has an additional advantage over the neural network. It allows one to trace the outward propagating wave front, potentially providing more information than strictly the source location, the probability of which is alone provided by the neural network. This is immediately valuable in distinguishing sources in close proximity.

Application of the image filter to the photospheric Doppler image time series of the MURaM simulation reveals that the acoustic sources are frequently found in and near intergranular lanes, particularly at those sites that contain complicated mixed flow structure or sudden local downflow enhancement. Multiple sources often occur in close proximity. Figure 5 displays the temporal evolution of the residual correlation map (top row), Doppler velocity (middle row), and pressure fluctuations (about the horizontal mean, bottom row) in a region with a comparatively isolated strong source. Even in this case in which one acoustic source is particularly strong, overlapping wave fronts from multiple close-by sources and from somewhat more distant sources can be seen. These form interference patterns in the residual correlation images. While the wave amplitudes are very low and noise plays some role in the images displayed, we have determined, using artificial and real simulation data and by adjusting the filter applied, that these patterns are not an artifact of the filtering method but instead very likely result from real wave interference. The filtering technique appears to provide a robust method for the identification of acoustic wave fronts emanating from sources that self-consistently arise in the convection simulation.

The sources are highly clustered on larger scales as well (see Figures 3 and 6). There are distinct regions where the acoustic emission is particularly loud (many sources are found in close spatial and temporal proximity) and others where it is quiet (few sources). In the simulation, this structuring appears to occur on mesogranular scales, scales that on the Sun would be comparable to the vertical substructure of the solar supergranulation (November 1989; Duvall & Birch2010), though the supergranular scale is absent from simulations (see Rast 2020, and references therein). To investigate this clustering, we constructed the residual convolutional map at several heights in the simulation, and found that acoustic excitation events are clustered around the locations of strong downflows at depth. The sources appear to be associated with the reconfiguration of the granular flows by deeper convergence of the intergranular plumes into large downflow structures. The amplitude of the residual convolutional signal is maximum quite deep in the photosphere, with weaker signal both above and below. This is visually apparent in Figures 6(a)–(c), and in Figure 6(d) we plot the fraction of total signal coming from each height (employing a depth-dependent sound speed in the
Green’s kernel convolution) integrated over the time series. The fractional emission \(\left(\frac{N}{N_0} \times 100\%\right)\), with \(N = \) total residual convolutional signal at given height and \(N_0 = \) total residual convolutional signal in the volume) peaks at depth of about 400–600 km below the photosphere, quite deep compared to estimates arising from the study of \(p\)-mode line asymmetries.

**Figure 5.** Snapshots of residual convolution maps (top) illustrating one main impulsive event along with multiple neighboring acoustic wave fronts propagating at the speed of sound in the MURaM photosphere at the \(\tau = 1\) plane. The corresponding Doppler velocity field and (center) pressure field (bottom) are shown as well, illustrating the complex dynamics at the source site.

**Figure 6.** (a)-(c) Variation of acoustic power (residual convolution signal, all with the same color table scaling) at different depths in the MURaM simulation. (d) Fractional emission (in percent \(N/N_0 \times 100\%\), where \(N = \) emission (residual convolution signal) at height \(h\) integrated over horizontal plane and time and \(N_0 = \) emission integrated over in the entire volume) with respect to height. The maximum fractional emission occurs at a depth of 400–600 km. (e) Vertical slice of the Doppler velocity in the MURaM simulation at the location of the strong source whose evolution is plotted in Figure 5 \((y = -2.194 \text{ Mm in the full domain, Figure 3})\) domain. The white dashed fiducial lines indicate the \(x\) and \(z\) event location, the site with the maximum residual convolution signal.
Emission from single very strong events also peaks at these depths indicating that the fractional emission peak is not just a function of event occurrence rate. Peak emission (maximum amplitude of the acoustic emission as measured by the residual convolutional signal) from the very strong acoustic event shown in Figure 5 occurs at a depth of about 480 km (indicated by the horizontal dashed fiducial line in Figure 6(c)). In this case the peak emission occurs as a result of the convergence, within the vigorous mesogranular downflow, of two supersonic granular plumes. Figure 7 plots the local Mach number of the flow in a small horizontal slice (3 pixel wide in x and 1 pixel thick in y) centered on the vertical dashed line in Figure 6(e), as a function of time. Two transonic downflows merge at the position and time of the acoustic event. Some previous studies have implicated hydrogen ionization as key to the formation of supersonic downflows and suggested that such downflows play an important role in acoustic excitation (Rast et al. 1993; Rast & Toomre 1993; Rast 2001). That seems to be borne out here, with the depth of the minimum of the adiabatic exponent \( \Gamma_1 = (d \ln P / d \ln \rho_{\text{had}}) \), horizontally averaged over each depth plane in the simulation, very close to that of maximum acoustic emission (green horizontal dotted line in Figure 7).

4. Reliability Tests

Convolutional filters carry some risk that the result one achieves is biased by the convolution one applies, that the pattern one is looking for is accidentally imprinted on the data. We performed a number of tests to help determine if this is the case in our analysis. In the simplest test, we applied both the neural network and the convolutional filter to a time series of MURaM photospheric Doppler images after scrambling the phases in time and space (phases randomized over a uniform distribution between 0 and 2\( \pi \)) while preserving the power at each spatial and temporal frequency. The neural network consistently returned a null detection of acoustic emission (confidence values less than 10%) when applied to this time series, and direct application of the convolutional filter produced some random circular patterns but none that propagated away from a compact site, as does the signal when it is the result of a local source. This suggests that the convolution is not imposing a defined pattern onto the solution, at least not when the modes are delta-correlated in time and space.

In another test, we trained the neural network using a particular sound speed in the Green’s function source kernel, and then applied it to data samples containing acoustic responses constructed using a range of propagation speeds. We did this both with and without the granulation noise. The network identified acoustic events with higher confidence when the sample sound speed was similar to that it was previously trained on. When the sound speed of the test samples deviated significantly from that of the training set, the network returned null detections. Moreover, when applied to the MURaM simulation data, the networks trained using kernels constructed with a sound speed close to that of the depth being analyzed produced higher confidences (for the neural network) or stronger amplitudes (for the convolutional filter) than those trained using a significantly different sound speed (\( c_s \pm 3 \text{ km s}^{-1} \)). Again this suggests that the signal being extracted is in the data, not imposed on it, that the network and the filter are identifying the physical wave response of the medium at the correct sound speed.

Finally, we explored the characteristics of the neural network based convolutional filter we constructed in Fourier space. Convolution with the acoustic Green’s function followed by application of the high frequency temporal differencing kernel reduces the low-frequency contributions of the granular flow while maintaining Fourier components with phase speeds that lie in the vicinity of the sound speed (bottom row, middle panel in Figure 8). The filter can be mimicked, to some degree, by constructing a very narrow passband filter on the \( k - \omega \) plane, one that filters out everything except high frequency components with phase speeds near the sound speed (bottom row, right-hand panel in Figure 8). When this Fourier filter is applied to the data it highlights events very similar to those found using the convolutional filter at the same locations in space and time, albeit with much higher noise levels. We note that this filter is very similar to that applied by Roth et al. (2010) and with visually quite similar results. The convolutional filter very effectively extracts from the data those Fourier components with phase speeds near the specified sound speed. Those modes have phase relations that corresponded to outward propagating pulses induced by acoustic source events (the Green’s function response).

Together these tests provide strong evidence that the convolution operator is not biasing the data to produce local wave-like propagation signals. Neither the neural network nor the direct application of the convolutional filter are prone to finding wave patterns in the granular noise field when there is no actual source present.

However, two additional sources of confusion can arise. The first source of confusion are the intermittent and random constructive wave interference sites. These can spuriously appear as local sources when the phase coherence between the waves is lost and the waves propagate away from the coherence site. Fortunately, in these occurrences the modes first come into and then lose coherence. They can thus be readily identified by their distinct time-reversible signature and eliminated as false sources. We note that the convolutional filter we are applying is dominated by high-spatial and high-temporal frequencies (Figure 8), well above those that characterize the solar p-modes. The potential spurious signal we are describing is caused by the interference of the local waves excited in a region of high source density, not by the intermittent local coherence of the global-modal oscillations. The second source of possible
Doppler map from the convolutional image time series from which the column were drawn, full MURaM Doppler same region after applying a simple MURaM. Center column: Residual convolution map. Right column: Map of or from an abrupt physical processes, such as the image time series. Such an impulse can result from confusion are any strong Dirac delta-function-like impulses in the image time series. Such an impulse can result from observational artifacts, such as cosmic ray hits on the detector, or from an abrupt physical processes, such as flaring events, if intensity images are being employed in the analysis. Convolving the Green’s function response (Equation (2)) with a spatially and temporally isolated bright or dark pixel (an effective delta function) yields the Green’s function response itself, and thus the false appearance of a wave propagating outward from the bright pixel location. Fortunately, these impulsive events can be clearly identified by careful analysis and work is in progress to mitigate their spurious contribution.

5. Conclusion

We have developed an image time series filter for the detection of local acoustic perturbations in simulated Doppler velocity images. We have achieved similar results, not described in this paper, using the continuum intensity and pressure fluctuation image time series. The neural network motivated convolutional filter we have described is quick to apply to images of arbitrary size and time series of arbitrary duration. It has no parameters to tune. Making the interpretive step away from the neural network itself allows direct application of the filter without the the need for the very large observational data sets required to train deep-learning algorithms; expressed in terms of human-understandable operations, the filter can be directly applied to observations without network retraining. Moreover, the interpretability of the filter allows us to test the range of its applicability and to tune it for optimum sensitivity when applying it to real observations. While it may be possible to improve the current version of the filter via architectural adjustments to the learning scheme of the neural network, and while the reliability of the filter should be tested over a wider range of simulations, given its initial performance on the simulation data, as described in this paper, we judge it likely to be already sufficiently robust to make significant contributions upon its initial application to real data.

Although we focused this work on photospheric source detection, using a two-dimensional approximation to the Green’s function, we were able to analyze height-dependent effects in the three-dimensional simulations by adjusting the kernel sound speed to match that of the depth of the layer being analyzed. Observations however are limited in the depth to which they can probe, and so while the two-dimensional Green’s function may be applied in the photosphere and above, upward in the solar atmosphere, it will not be useful in identifying the location of deeper sources, particularly those at the depth of peak emission suggested by our work. However, the photospheric signal of the true three-dimensional Green’s function is sensitive to the source depth. Employing it and the techniques we have developed here may allow the determination of both the location and depth of source events using high-cadence high-resolution Doppler measurements at one or more heights in the observable solar photosphere. Fortuitously, the observational capabilities required for these efforts are just now becoming available with the commissioning of the National Science Foundation’s DKIST.

The implications of this work extend beyond identification and characterization of the source of the solar p-modes. As examples, measuring the nonuniform source distribution in the photosphere may lead to an understanding of the spatially inhomogeneous propagation of energy and momentum into the chromosphere and consequent observable footprints in the wave flux and power spectra measured there, and the ability to carefully measure the very high-spatial and temporal frequency local propagating wave front induced by real sources may open up a new era in high-resolution local helioseismological sounding of small-scale structure in the photosphere.

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Appendix A
Neural Network Architecture

The network we employ has a convolutional architecture, which applies a series of convolutions with a combination of small and large kernels (to be inferred during the training) to
the input data at each layer. The neural network was developed using the Keras Python library with the Tensorflow back end, and executed on Dual NVIDIA Quadro P5000 16 Gbyte GPUs. All inputs were normalized to the interval \([-1, 1]\) in the training set. The training was carried out by minimizing the “binary crossentropy” loss function via an Adam stochastic first-order gradient-based optimization algorithm (Kingma & Ba 2014) with an adaptive learning rate. As for any stochastic optimization method, the gradient was estimated from subsets of the input samples, also known as batches. We used batches of two samples and trained the network for 50 epochs, thus each training instance runs 12.5 million iterations to convergence.

The network architecture:

1. Input: This layer represents the input images of size \(N_t \times N_x \times N_y\). Consequently, it accepts tensors of \(N_t\) image sequences each \(N_x \times N_y\) in size.

2. Convolution I, \(n_t \times 5 \times 5\): This layer represents four-dimensional convolutions with a set of 64 kernels (channels) \(N_{input} \times n_t \times 5 \times 5\) in size. We iteratively determined the number of kernels and their size to provided best inference, with the network still being trained very fast using the GPUs. The output tensors of these layers are \(64 \times N_t \times N_x \times N_y\) in size.

3. Maxpool, \(1 \times 4 \times 4\): This layer simply downsamples the output from the previous layer, reducing its spatial dimension and allowing for assumptions to be made about features contained in the subregions binned. The output tensors of this layer are \(64 \times N_t \times N_x/4 \times N_y/4\) in size.

4. Convolution II, \(n_t \times 3 \times 3\): Another layer of four-dimensional convolutions with a set of 32 kernels (channels) \(N_{input} \times n_t \times 3 \times 3\) in size. Again, we iteratively determined the number of kernels and their size to provided best inference within the limits of performance. The output tensors of these layers are \(2048 \times N_t \times N_x/4 \times N_y/4\) in size.

5. Maxpool, \(1 \times 2 \times 2\): Another layer that downsamples the output spatial dimension further, resulting in output tensors \(2048 \times N_t \times N_x/8 \times N_y/8\) in size.

6. Flatten: This layer flattens the output from the previous layer to a one-dimensional array. Hence, the dimension of the output array of this layer is \((2048 \times 3 \times N_x/8 \times N_y/8, 1)\).

7. Fully connected, 10 neurons: A fully connected layer of 10 neurons with tanh activation, which implements the operation: \(\text{activation}(\text{out}_{\text{flatten}} \cdot W + b)\), where activation is the element-wise activation function passed as the activation argument, \(W\) is a weights matrix created by the layer, and \(b\) is a bias vector created by the layer.

8. Output, 1 neuron: A single neuron fully connected with the previous layer and activated with soft-max activation to calculate the probability of the target. The range of the output in the neuron is 0–1 as this layer returns the confidence of whether an acoustic emission occurs or not.

Appendix B

Training Set for Neural Network

The MURaM photospheric data can be thought of as being composed of three intrinsic components, where two of these are dominant, the convective motions and the modal oscillations, and the third is faint, the wave field produced by local sources. The dominant components are shown in Figure 9. Since the simulated photosphere itself has sites of acoustic emission, the data set for training the neural network needs to be sanitized in such a way to diminish the contribution of the acoustic emission events.

One way to achieve this is to filter the MURaM photospheric data 2 km s\(^{-1}\) (as determined by empirical testing on idealized sources) below the sound speed limit of the typical subsonic filter (Title et al. 1989) leaving only the granular motion, and then adding a random mixture of all the allowed modal oscillations in the simulation box. The resulting composite Doppler map includes only very limited contributions from any source that induces an acoustic pulse as its Fourier contribution is concentrated along the constant phase speed line in the \(k–\omega\) diagram. It can be used as a source-free template.

Similar result can be achieved using deep-learning algorithms as well. We experiment with a convolutional variational autoencoder, which is essentially a generative model that learns separately the granular motion and the modal oscillations. For such cases, two data sets, one filtered 2 km s\(^{-1}\) below the sound speed limit and one filtered 2 km s\(^{-1}\) above (such as Figure 9 right panel), are prepared and used to train two individual generative autoencoders. The generated granular motion and the modal oscillations are then mixed with appropriate amplitudes and the final training data is produced. This composite Doppler map is found to be predominantly source-free and can be used as a source-free template as well.

We explored the performance of augmented data sets produced by both methods described above, and achieved similar outcomes, concluding that both methods are equally viable.
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Figure 9. Top: MURaM photospheric Doppler map (left), granular motion (centered) filtered at $\tau = 1$ sound speed, and the remaining modal oscillations (right). Bottom: corresponding $k - \omega$ diagrams.
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