

Segmentation of the F2 Leading Edge in a Backscatter Sounder Ionogram

Rafal Sienicki, Manuel A. Cervera, Philip H. W. Leong

Abstract—Backscatter sounder systems co-located with Over-the-Horizon Radar (OTHR) can be leveraged to provide a near real-time characterisation of the ionospheric propagation conditions to aid the OTHR surveillance mission. Ionogram inversion can be performed using features derived from a backscatter ionogram to infer the optimum OTHR operational parameters and to enable the geolocation of the detected targets. In this paper, we demonstrate the application of a deep learning segmentation model on a backscatter ionogram dataset obtained from the Jindalee Operational Radar Network (JORN) frequency management system to extract the F2 leading edge feature. Our results show that deep learning is a viable method for leading edge feature identification and extraction in backscatter ionogram imagery.

Index Terms—Ionogram scaling, ionosphere, segmentation, Over-the-Horizon Radar.

I. INTRODUCTION

THE ionosphere is a region of the Earth's atmosphere that contains free electrons and is able to refract High Frequency (HF)¹ (3-30 MHz) radio waves. An OTHR exploits this feature to provide a long range, beyond line-of-sight surveillance capability. The ionosphere is a highly dynamic medium that varies temporally and spatially over many different scales, hence characterisation of the ionosphere is crucial for the effective operation of an OTHR.

Ionospheric sounder equipment is used to measure and quantify the properties of the ionosphere by the transmission and reception of HF radio waves. Vertical Incidence Sounder (VIS) and Oblique Incidence Sounder (OIS) systems are commonly used for this purpose. A VIS measures the ionospheric properties directly above it (the transmitter and receiver are co-located), whilst an OIS measures the ionospheric properties at the mid-point between a transmitter and receiver separated by several hundred or thousands of kilometers. A key challenge for the use of VIS and OIS systems to support OTHR operation is to ensure the sounder measurement footprints overlap with OTHR coverage requirements. However, physical, practical

Rafal Sienicki and Manuel A. Cervera are with the Defence Science and Technology Group, Edinburgh, SA 5111, Australia (email: rafal.sienicki@defence.gov.au)

Manuel A. Cervera is also associated with The School of Physics, Chemistry and Earth Sciences, The University of Adelaide, SA 5000

Philip H. W. Leong is with the School of Electrical and Information Engineering, The University of Sydney, NSW 2006, Australia (email: philip.leong@sydney.edu.au)

Manuscript received mm dd, YYYY; revised MM DD, YYYY.

¹Ionospheric effects on radio wave propagation are not exclusive to this band i.e. propagation effects occur at frequencies both below and above the HF band limits.

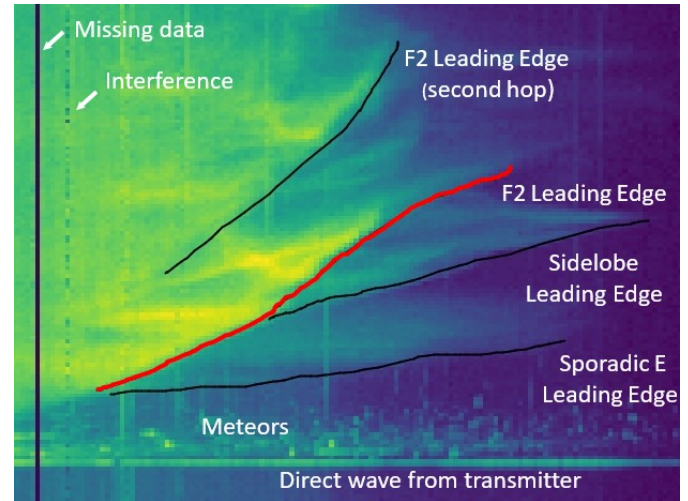


Fig. 1: Cropped sample backscatter sounder ionogram image showing labelled dominant features. The image represents return signal strength as a function of group range (vertical axis) and radio wave frequency (horizontal axis). The F2 leading edge (red line) is used as a target for the supervised segmentation training presented in this research. Returns from meteors, interference signals and missing data pixels are also shown.

and legal constraints on sounder transmitter and receiver placement may render the sounder network sub-optimal for OTHR application. In this situation, a Backscatter Sounder (BSS) is more suitable for the OTHR use-case. The quasi co-location of receiver and transmitter systems and similar two-way propagation mode of the BSS and OTHR systems makes the BSS attractive for OTHR application [1] [2].

The return signal strength recorded by ionospheric sounders, when displayed as a function of group range² vs radio wave frequency, is known as an ionogram. An example of a BSS ionogram is presented in Figure 1. These ionograms are evaluated to identify critical features and parameters that subsequently can be used to estimate the electron density vertical profile. This process is known as ionogram scaling³.

²Time-of-flight of the radio wave multiplied by the speed of light in vacuo.

³In this paper, the term 'scaling' is used in reference to all ionograms recorded by VIS, OIS and BSS sounders. The authors acknowledge that the term does not have the same meaning for BSS and VIS/OIS ionogram categories. In the latter case, scaling refers to feature identification and parameterisation of ionospheric properties. This is the conventional interpretation of the term in the ionospheric research community. In the former case, the term refers to a more limited capability. Here, scaling refers to the identification of features from which information regarding propagation modes may be inferred, without any subsequent ionospheric parameterisation.

Sienicki et al. [3] reviews ionogram features and scaling techniques for different ionospheric sounders. Traditionally, ionogram scaling has been performed by ionospheric subject matter experts; however, manual scaling is a time intensive and laborious activity and hence numerous automatic scaling techniques have been investigated and developed over the last few decades. The vast majority of automated scaling algorithms have been applied to VIS ionograms, and to a lesser extent, OIS ionograms, with limited attention to BSS ionograms [3]. The scaling of BSS ionograms is more challenging and the least mature. The integration of returns from multiple propagation modes and antenna sidelobes, the variable ground backscatter, and the reduced number of non-ambiguous visually discernible image features increases the scaling complexity.

The Leading Edge (LE) is the primary feature of interest of a BSS ionogram. A LE is a thin, ledge-like feature that is visually discernible as a series of connected, steep signal strength (pixel intensity) changes. It is the minimum time delay (group range) for the receipt of the backscattered, ionospherically propagated signal as a function of frequency [4]. Typically, the LE trace exhibits a smooth, low-order polynomial-like profile with the contour line trending upwards as a function of frequency. Each group range coordinate on the LE trace corresponds to a unique ground range for the backscattered ray(s) with respect to frequency.

Multiple LE traces, corresponding to propagation via different propagation modes, are commonly observed on a BSS ionogram. Key LE features are labelled in the backscatter ionogram depicted in Figure 1. The LE trace associated with returns from the F2 ionospheric layer, referred to as F2LE, is the most important BSS ionogram feature that is critical for ionogram inversion. The F2LE is labelled as a red trace in Figure 1.

In this work, we train a deep learning segmentation model, the U-Net [5] model, on a labelled JORN BSS ionogram dataset to demonstrate an automated single-hop F2LE feature extraction functionality. Our research demonstrates that a novel loss function based on Focal and Negative Log Likelihood loss terms is optimal for BSS ionogram F2LE segmentation. This loss function delivers a 78.9 km group range scaling error with a 93.9% recall rate on the JORN BSS dataset.

II. RELATED WORKS

Ionogram scaling features are visually discernible as a series of curved, connected trace segments representing a pattern of signal strength variation that is governed by ionospheric propagation conditions. Visual discernment of the critical features in ionograms is complicated by noise, interference, sounder equipment failures, returns from “unusual” ionospheric layers (e.g. sporadic E layer) and ionospheric disturbances. The effects of these phenomena can be observed on an ionogram as distortion, smearing, blurring and masking of important ionogram features. Consequently ionogram scaling is a challenging task, particularly for ionograms captured in disturbed ionospheric conditions.

A significant amount of research has been conducted into automatic scaling for VIS and OIS ionograms over the last

few decades. Techniques such as data fitting [6], [7], template matching [8], [9], computer vision [10], [11], Kalman filtering [12], fuzzy logic [13] and more recently, machine learning [14]–[17] have been investigated for automatic scaling. This research has produced a number of automatic scaling tools. ARTIST [6], Autoscala [18] and DST-IIP [9] are example scaling tools that have been demonstrated to reliably extract features in VIS ionograms. For the OIS case, there is a reduced number of scaling tools; however, details of several algorithms have been published [9], [10], [19], [20]. Sienicki et al. [3] provides a comprehensive review of the automatic scaling techniques and tools.

The BSS is significantly larger, more complex and expensive than the VIS and OIS, hence it is not as common and there is no publically available BSS dataset. Consequently, the scaling of BSS ionograms is the least mature.

Identification and extraction of LE features in a BSS ionogram is a challenging undertaking. Firstly, the LE is a ledge-like feature with undefined start or end points. It does not resemble visually discernible features such as cusps, asymptotic lines or vertices that are present in VIS and OIS ionograms. Secondly, the effects of ionospheric dynamics and sounder characteristics can profoundly influence the LE feature. Consequently, the LE may exhibit intensity variation that can render some aspects of the trace line to be faint, disconnected, or exhibit localised strong curvature features, e.g. kinks. Thirdly, discrimination logic is required to separate the LE traces based on refractions from different ionospheric layers (including multiple hops). This is complicated by apparent LE features associated with azimuthal sidelobes of the receive array beamformer.

There are very few publications covering investigations for BSS ionogram scaling with no authoritative scaling tools matching the pedigree of VIS scaling tools such as ARTIST. Techniques based on the Kalman filter [21], minimum group path theory [22], [23], polynomial line fitting [22], image processing [24] and machine learning [17] [25] are the main approaches investigated. In many cases, these investigations are conducted on datasets recorded by a low power BSS.

In this work, we apply a deep learning model on a dataset recorded by a high power BSS system. Higher power increases the signal-to-noise ratio, which reveals more ionospheric features within the ionograms. This can reveal complications such as contributions from the receive array sidelobes, which may be problematic for automated scaling algorithms.

III. DATASET

Data collected from two BSS sub-systems of the Royal Australian Air Force (RAAF) JORN Frequency Management System (FMS) [5] are used in this study. Each sounder performs measurements for 8 azimuthal beams covering a 90° field-of-regard, spanning a frequency bandwidth of 5–45 MHz, with a 200 kHz and 50 km frequency and range resolution respectively [1]. The measurement data originates from the year 2014 spanning a range of diurnal and seasonal conditions.

A total of 1000 ionogram images from the JORN FMS dataset are used as a basis for this investigation. The first

hop F2LEs were manually labelled by DST Group senior and junior ionospheric specialists to enable supervised segmentation model training. The trace label is a continuous line with arbitrary start and end points. An example of a labelled BSS ionogram is presented in Figure 1. For this study, only the F2LE label is used (red line) as a target signal.

The ionogram images were formatted into a 697x924 pixel image size, converted into greyscale format and normalised. The x-y coordinates of the F2LE label were used to generate a pixel level, binary mask.

IV. METHOD

We treat the F2LE identification and extraction task as a supervised segmentation challenge. In this work, we apply a deep learning Fully Connected Convolutional (FCN) encoder-decoder U-Net architecture that has achieved success in the biomedical field [5].

In many deep learning image segmentation investigations it is common to use the distribution based Binary Cross Entropy (BCE) and/or region based soft Dice Loss (DL) functions for model training [26]. These loss functions demonstrate good performance for segmentation of natural and medical targets. However, one drawback for this type of loss function design is that the shape or contour of the target is not taken into consideration. It has been found that such a loss function design is not suitable for application to images that contain ambiguous or discontinuous boundaries [27].

To address this limitation, we use a distance map to capture the shape and geometrical profile of the thin, one-dimensional BSS ionogram F2LE feature. A distance map is a matrix, with the same dimensions as the original input image, that stores the values of the Euclidean distance of each pixel to the closest point on the target mask, defined in the two-dimensional image coordinate space. The distance map is queried to determine distance information for each pixel of interest during loss calculations. Figure 2 shows a sample of a F2LE distance map mask that is used for model training in this investigation. The generation of distance map is a computationally expensive task; however, this task only needs to be performed once, and can be performed offline.

We apply a scaled Negative Log Likelihood (NLL) function to enable the U-Net model to learn the segmentation of the F2LE feature. The pixel-wise distance map is used to derive mean and standard deviation parameters of the Normal distribution. This function is used to guide the model to produce a segmentation output that is as close as possible to the F2LE label. The scaling factor is applied to avoid penalisation of segmentation outputs that are close to the truth label, but exhibit higher variance. The equation of the scaled NLL function is defined in Equation 1:

$$\mathcal{L}_{sNLL} = -\log \left(\frac{\sigma}{\mu \sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{-\mu}{\sigma} \right)^2} \right) \quad (1)$$

where μ and σ are respectively the mean and standard deviation of the pixel-wise distance distribution of a segmentation prediction. The NLL function acts to impose a higher loss penalty for predictions that are distant from the labelled F2LE trace.

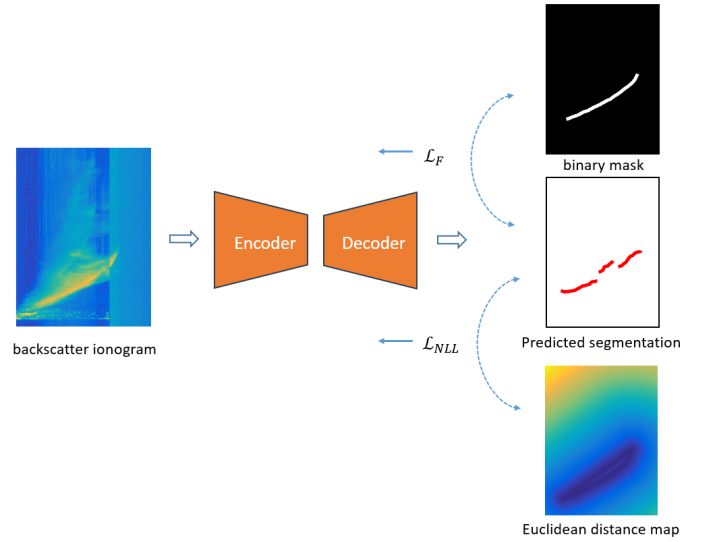


Fig. 2: In this investigation, a U-Net encoder-decoder model is used to segment the F2LE feature. The model accepts a backscatter ionogram as input. A binary mask derived from manual labels is used to compute the focal loss component. A Euclidean distance map (based on the binary mask) is used to derive a pixel-wise NLL distribution loss component.

This is in contrast to the DL function, a popular segmentation loss function, that solely takes into account the degree-of-overlap without consideration of pixel distance.

To account for the highly imbalanced nature of our dataset, we integrate a Focal Loss (FL) term into our loss function, a variant of the BCE function that is designed for application in highly imbalanced datasets [28]. A lower loss term is imposed on background pixels to enable increased focus on rare, foreground pixels. The FL function is defined in Equation 2:

$$\mathcal{L}_F = -1 (1 - p_t)^\gamma \log(p_t) \quad (2)$$

where p_t is the estimated pixel probability and γ is a tunable focussing parameter.

The loss function for the F2LE segmentation model is composed of focal and NLL terms as follows:

$$\mathcal{L} = \mathcal{L}_F + \mathcal{L}_{sNLL} \quad (3)$$

An architecture diagram of our design is presented in Figure 2.

V. EXPERIMENTATION AND METRICS

We apply a 10-fold cross validation scheme with a 90% train-test split on the dataset to ensure our model does not overfit on the relatively small dataset.

Table I outlines the main model hyper-parameters that were used in our experimentation. These parameters were derived using a manual grid search approach.

Unlike the VIS⁴ ionogram case for which a scaling standard exists [29] and is used in many automatic VIS scaling

⁴Whilst no such standard exists for the OIS case, the similarity of features in OIS and VIS ionograms, deems it acceptable for the same standard to be applied to the OIS ionogram case.

Parameter	Value
batch size	4
number of epochs	200
learning rate	1e-4 reduced to 1e-7, using a cosine annealing learning rate scheduler
Focal loss focussing parameter γ	2
mask threshold	0.5

TABLE I: Model hyper-parameters used in this investigation.

tools to report scaling performance, no equivalent standard exists for the BSS ionogram scaling application. An obvious metric is based on the pixel-wise distance between the estimated and truth (manually labelled) LE traces. Given that a BSS ionogram LE trace exhibits an undefined length with no fixed start or end coordinates, a decision needs to be made on how many, and which LE pixels should be used as reference pixels for metric calculations.

In this work, we use a BSS ionogram scaling domain specific metric to evaluate segmentation performance. The scaling error is reported in the ionogram group range domain in terms of accuracy and recall scores. These scores are calculated for a sample of OTHR frequency values. In this investigation, we report a group range scaling error for the following frequencies: 10MHz, 13MHz, 16MHz, 19MHz and 22MHz. This evaluation frequency bandwidth overlaps with the majority of the F2LE trace segments considered in the dataset used for this investigation. The evaluation frequency values are marked as dotted vertical lines in the sample ionogram segmentation results shown in Figure 3.

Accuracy is defined as the mean pixel-wise distance between the estimated and truth LE pixels. This is reported as a group range scaling error for each evaluation frequency.

The recall metric quantifies the relative number of segmentation results reported by a segmentation model, and can be used to infer the number of missed (False Negatives) F2LE detections. In this investigation, a missed F2LE detection is reported for the case when no F2LE pixels are returned by the segmentation model for an evaluation frequency.

For both accuracy and recall metric calculations, a mean score is reported. This reflects the average performance based on the five evaluation frequencies in each ionogram, evaluated on the test dataset. To ensure a consistent and repeatable evaluation, all five reference pixel coordinates⁵ in each test ionogram are used to calculate the metric scores.

VI. RESULTS AND DISCUSSION

Table II details the results from our experiments conducted on the JORN BSS dataset. The table displays segmentation performance in terms of group range scaling error and recall metrics for different loss function configurations. A U-Net segmentation model configured with a loss function composed of NLL and FL terms achieves the best result in terms of group

⁵For ionograms that did not include a LE pixel for the referenced group range evaluation line, a reduced number of evaluation LE pixels was used.

U-Net Loss function	Mean Group Range Scaling Error (km)	Mean Recall (%)
wBCE	88.7	89
wBCE + DL	93.8	44.6
FL	87.0	94.2
wBCE + sNLL	86	89.4
FL + NLL	84.9	94.1
FL + sNLL	78.9	93.9

TABLE II: F2LE segmentation experiment results. Mean group range scaling and recall performance with respect to 5 evaluation frequencies is presented. *wBCE* = *weighted Binary Cross Entropy*, *DL* = *Dice Loss*, *NLL* = *Negative Log Likelihood*, *sNLL* = *scaled Negative Log Likelihood*, *FL* = *Focal Loss*.

range scaling performance. This model also has a high level of recall.

Inspection of the segmented F2LE trace generated for the BSS ionogram test dataset reveals that in the majority of cases the LE trace is segmented correctly. The segmented LE pixels are consistent with the human labelled F2LE trace. The first (top) image presented in Figure 3 represents a good F2LE segmentation result. In this ionogram, the segmented F2LE trace overlaps closely with the labelled F2LE trace, including frequency evaluation pixels (identified as vertical dotted lines). The second ionogram in Figure 3 also produces acceptable segmentation results referenced to the evaluation pixels; however, the performance is slightly reduced relative to the top ionogram, and certain aspects of the LE trace are disconnected.

Analysis of the results indicates that for some cases, aspects of the F2LE trace are incorrectly segmented. Many of these False Positive errors correspond to instances where the model identifies a leading edge of non-F2 ionospheric layers, higher order F2 hops or sidelobe returns as an F2LE pixel. The bottom ionogram in Figure 3 is an example where a portion of the sidelobe leading edges are falsely segmented as an F2LE. It is expected that training the model on a larger dataset will improve the model's ability to segment and discriminate LE pixels correctly for ionograms captured in wider set of ionospheric conditions.

The results also confirm that the segmentation performance is robust to ionogram interference and missing data artefacts.

Table II also includes results from our experimentation for different loss functions, including cross-entropy and dice loss functions that are commonly applied for image segmentation. The results show that NLL and FL functions enhance the U-Net segmentation model's group range scaling performance. The fusion of these loss terms in a loss function (FL + NLL) acts to draw segmentation pixels closest to the single-hop F2LE, generate thin trace segments and minimise the number of FP outputs that are not associated with edge features corresponding to a single-hop F2LE. The table also highlights the effect of the scaling factor to the NLL term on improving the group range scaling performance.

The results shown in Table II also confirm that the DL function is not suited for the BSS ionogram LE segmentation

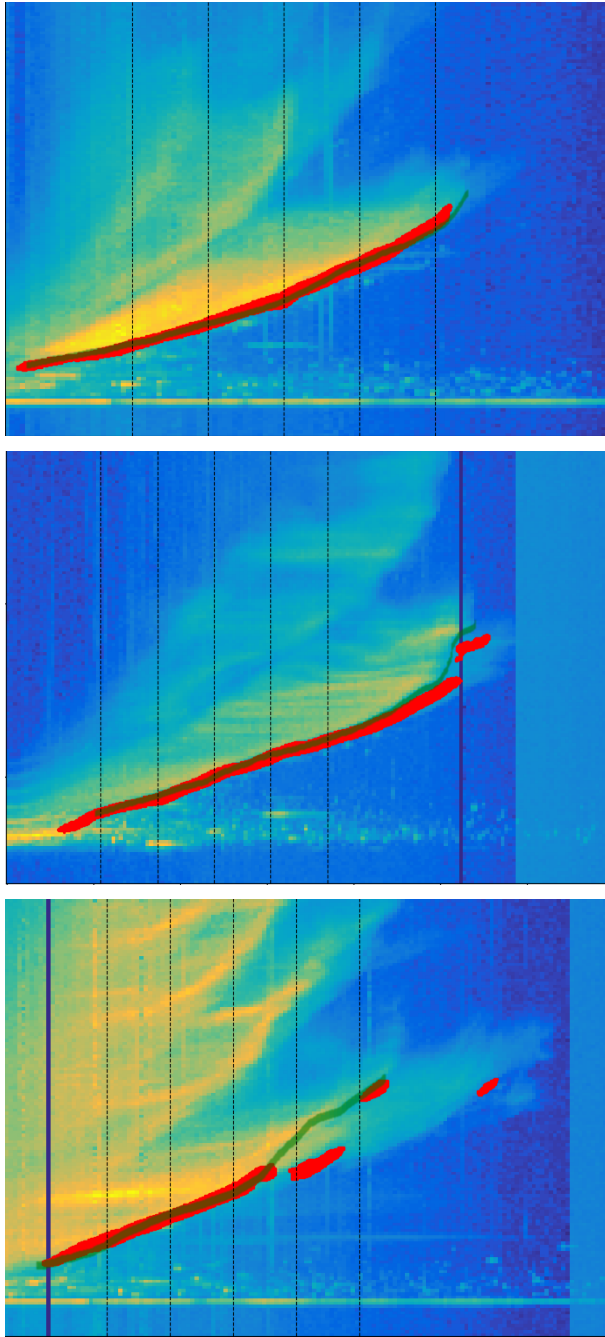


Fig. 3: Sample cropped BSS ionogram from the test dataset showing results from our deep learning segmentation model. Green trace = human labelled F2LE trace. Red trace = U-Net model F2LE segmentation output. Dotted vertical lines = five reference frequency values used to quantify F2LE group range scaling error. *Top image*: This represents a good segmentation result. The majority of extracted F2LE trace lies close to the truth F2LE trace. *Middle image*: Good segmentation results returned for all group range line evaluation pixels; however, some aspects of the F2LE trace are disconnected. *Bottom image*: Good segmentation result for the F2LE trace; however, some aspects of the sidelobe leading edge are also (falsely) classified as F2LE.

application. In contrast to the performance improvement observed for the use of the DL function, when applied to object segmentation [30], we observe a performance degradation for the BSS ionogram dataset. This result indicates that an Intersection over Union (IoU) based loss function may not be suitable for segmentation of a BSS ionogram LE feature.

VII. CONCLUSION

In this paper, we have applied the U-Net image segmentation model to the backscatter sounder data from the JORN. Experimental results show that our approach has been successful in extracting the single-hop F2LE feature in backscatter ionogram images that include LE traces related to multiple propagation modes and antenna sidelobes, and interference signals.

This model can be extended to perform feature extraction of leading edges corresponding to E, Es (sporadic E), F1, higher order hops and sidelobe returns.

Future work will consider a larger dataset and integration of radio wave propagation theory and ionospheric physics with deep learning to produce a physics guided deep learning backscatter ionogram scaling model.

ACKNOWLEDGMENTS

This work would not have been possible without access to a labelled ionogram dataset. We thank Danielle Edwards for the time taken to perform the laborious task of labelling hundreds of backscatter ionogram images.

We thank Lenard Pederick, Chris Crouch, David Netherway and Barry Flower for useful discussions and suggestions to support this research investigation.

AUTHOR INFORMATION

Rafal Sienicki received the B.E. in computer systems engineering from the University of South Australia in 2002. In 2005 he joined the Defence Science and Technology Group where he is currently a research scientist. He is currently pursuing the Ph.D. degree with The University of Sydney. His current research interests include modelling, simulation and experimentation, electronic warfare, radar, and machine learning.

Manuel A. Cervera received the B.Sc. (Hons.) and Ph.D. degrees from the Physics Department, The University of Adelaide, Adelaide, SA, Australia, in 1990 and 1996, respectively. He is a Senior Scientist and the Discipline Leader for HF Radar Performance and Environment in the HF Systems science and technology capability area at the Defence Science and Technology Group, Edinburgh, SA, Australia. Since 2018, he is also an Adjunct Associate Professor with the Space and Atmospheric Physics Group, School of Physical Sciences, The University of Adelaide. His research interests include ionospheric physics, radio wave propagation through the ionosphere, HF radio systems, and performance modeling of over-the-horizon radar.

Philip H. W. Leong Philip Leong received the B.Sc., B.E. and Ph.D. degrees from the University of Sydney. From 1997-2009 he was with the Chinese University of Hong Kong. He

is currently Professor of Computer Systems in the School of Electrical and Computer Engineering at the University of Sydney, Chief Technology Officer at CruxML and Chief Executive Officer at TernaryNet. His research interests include FPGA architectures and applications, computer architecture and machine learning.

REFERENCES

- [1] G. F. Earl and B. D. Ward, "The frequency management system of the jindalee over-the-horizon backscatter hf radar," *Radio Science*, vol. 22, no. 2, pp. 275–291, 1987. [Online]. Available: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/RS022i002p00275>, eprint=<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/RS022i002p00275>
- [2] S. V. Fridman, "Reconstruction of a three-dimensional ionosphere from backscatter and vertical ionograms measured by over-the-horizon radar," *Radio Science*, vol. 33, no. 4, pp. 1159–1171, 1998. [Online]. Available: <https://doi.org/10.1029/98RS00477>
- [3] R. Sienicki, D. J. Edwards, M. A. Cervera, and P. H. W. Leong, "Ionogram scaling for vertical, oblique, and backscatter sounders: A review of challenges and opportunities," *IEEE Geoscience and Remote Sensing Magazine*, pp. 2–22, 2025.
- [4] T. A. Croft, "Sky-wave backscatter: A means for observing our environment at great distances," *Reviews of Geophysics*, vol. 10, no. 1, pp. 73–155, 1972. [Online]. Available: <https://doi.org/10.1029/RG010i001p00073>
- [5] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," pp. 234–241, 10 2015.
- [6] B. W. Reinisch and H. Xueqin, "Automatic calculation of electron density profiles from digital ionograms: 3. processing of bottomside ionograms," *Radio Science*, vol. 18, no. 3, pp. 477–492, 1983. [Online]. Available: <https://doi.org/10.1029/RS018i003p00477>
- [7] M. W. Fox and C. Blundell, "Automatic scaling of digital ionograms," *Radio Science*, vol. 24, no. 6, pp. 747–761, 1989. [Online]. Available: <https://doi.org/10.1029/RS024i006p00747>
- [8] C. Jiang, G. Yang, Z. Zhao, Y. Zhang, P. Zhu, and H. Sun, "An automatic scaling technique for obtaining f2 parameters and f1 critical frequency from vertical incidence ionograms," *Radio Science*, vol. 48, no. 6, pp. 739–751, 2013. [Online]. Available: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2013RS005223>, eprint=<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2013RS005223>
- [9] A. J. Heitmann and R. S. Gardiner-Garden, "A robust feature extraction and parameterized fitting algorithm for bottom-side oblique and vertical incidence ionograms," *Radio Science*, vol. 54, no. 1, pp. 115–134, 2019. [Online]. Available: <https://doi.org/10.1029/2018RS006682>
- [10] N. J. Redding, "Image understanding of oblique ionograms: the autoscaling problem," in *1996 Australian New Zealand Conference on Intelligent Information Systems. Proceedings. ANZIS 96*, Conference Proceedings, pp. 155–160.
- [11] Z. Chen, S. Wang, S. Zhang, G. Fang, and J. Wang, "Automatic scaling of f layer from ionograms," *Radio Science*, vol. 48, no. 3, pp. 334–343, 2013. [Online]. Available: <https://doi.org/10.1002/rds.20038>
- [12] F. Su, Z. Zhao, S. Li, M. Yao, G. Chen, and Y. Zhou, "Signal identification and trace extraction for the vertical ionogram," *IEEE Geoscience and Remote Sensing Letters*, vol. 9, no. 6, pp. 1031–1035, 2012.
- [13] L.-C. Tsai and F. T. Berkeley, "Ionogram analysis using fuzzy segmentation and connectedness techniques," *Radio Science*, vol. 35, no. 5, pp. 1173–1186, 2000. [Online]. Available: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/1999RS002170>, eprint=<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/1999RS002170>
- [14] V. Mochalov and A. Mochalova, "Extraction of ionosphere parameters in ionograms using deep learning," *E3S Web of Conferences*, vol. 127, p. 01004, 2019.
- [15] C. De La Jara and C. Olivares, "Ionospheric echo detection in digital ionograms using convolutional neural networks," *Radio Science*, vol. 56, no. 8, p. e2020RS007258, 2021, e2020RS007258 2020RS007258. [Online]. Available: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2020RS007258>, eprint=<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2020RS007258>
- [16] Z. Xiao, J. Wang, J. Li, B. Zhao, L. Hu, and L. Liu, "Deep-learning for ionogram automatic scaling," *Advances in Space Research*, vol. 66, no. 4, pp. 942–950, 2020. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S027311772030332X>
- [17] J. Xue, C. Zhang, B. Yin, X. Jia, J. Xu, and M. Ma, "Ionogram echo extraction based on the convolutional neural networks," *Radio Science*, vol. 57, no. 6, p. e2022RS007459, 2022, e2022RS007459 2022RS007459. [Online]. Available: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2022RS007459>, eprint=<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2022RS007459>
- [18] C. Scotto, "A method for processing ionograms based on correlation technique," *Physics and Chemistry of the Earth, Part C: Solar, Terrestrial Planetary Science*, vol. 26, no. 5, pp. 367–371, 2001. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1464191701000150>
- [19] A. Ippolito, D. Altadill, C. Scotto, and E. Blanch, "Oblique ionograms automatic scaling algorithm oiasa application to the ionograms recorded by ebro observatory ionosonde," *J. Space Weather Space Clim.*, vol. 8, 2018. [Online]. Available: <https://doi.org/10.1051/swsc/2017042>
- [20] Y. Hu, H. Song, X. Zou, and Z. Zhao, "Real-time automatic scaling method of oblique ionogram parameters based on morphological operator and inversion technique," *Wuhan University Journal of Natural Sciences*, vol. 20, no. 4, pp. 323–328, 2015. [Online]. Available: <https://doi.org/10.1007/s11859-015-1100-2>
- [21] S. T. Hutchinson, "Scaling backscatter 1F leading edges," Internal Report, DST Group, 1994.
- [22] H. Song, Y. Hu, C. Jiang, C. Zhou, and Z. Zhao, "Automatic scaling of hf swept-frequency backscatter ionograms," *Radio Science*, vol. 50, no. 5, pp. 381–392, 2015. [Online]. Available: <https://doi.org/10.1002/2014RS005621>
- [23] M. S. Penzin, S. N. Ponomarchuk, V. P. Grozov, and V. I. Kurkin, "Real-time techniques for interpretation of ionospheric backscatter sounding data," *Radio Science*, vol. 54, no. 5, pp. 480–491, 2019. [Online]. Available: <https://doi.org/10.1029/2018RS006656>
- [24] M. McDonnell, "Wavelet based detection and fitting of backscatter ionogram leading edges," 2014.
- [25] J. Ma, G. Yang, C. Jiang, and T. Liu, "Pattern recognition and leading edge extraction for the backscatter ionograms by yolox," *Wuhan University Journal of Natural Sciences*, vol. 30, pp. 69–78, 2025.
- [26] J. Ma, J. Chen, M. Ng, R. Huang, Y. Li, C. Li, X. Yang, and A. Martel, "Loss odyssey in medical image segmentation," *Medical Image Analysis*, vol. 71, p. 102035, 2021.
- [27] F. Caliva, C. Iriondo, A. Morales Martinez, S. Majumdar, and V. Pedoia, *Distance Map Loss Penalty Term for Semantic Segmentation*, 2019.
- [28] T. Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár, "Focal loss for dense object detection," in *2017 IEEE International Conference on Computer Vision (ICCV)*, Conference Proceedings, pp. 2999–3007.
- [29] W. R. Piggott and K. Rawer, "U.R.S.I. handbook of ionogram interpretation and reduction," 1978, (Karl). [Online]. Available: <https://repository.library.noaa.gov/view/noaa/10404>
- [30] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-net: Fully convolutional neural networks for volumetric medical image segmentation," in *2016 fourth international conference on 3D vision (3DV)*. Ieee, Conference Proceedings, pp. 565–571.