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三、陳博士畢業論文題目「深度學習與調適性偵測技術應用於SeaSonde高頻測流雷達之船舶回波識別與追蹤」（英文版），按本會「國防工業獎學金發放作業規定」第五點獎學金受領人義務(三)規定，提供畢業論文2本及電子檔，並於論文致謝誌中表達對本會之感謝。另按同規定第七點成果運用，畢業論文無償提供本會或本會指定之公法人、政府機關（構）運用。（如附呈2）

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Vessel Echoes Recognition and Tracking of SeaSonde HF Radar Based on Deep Learning and Adaptive Signal Identification Fusion Processing

by

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ABSTRACT

The 1982 "United Nations Convention on the Law of the Sea" stipulates that the sovereign states have the right to the exploration and utilization of marine resources in their exclusive economic zone (EEZ). Facing the challenge of maritime surveillance for prevention of illegal conduct on the extensive ocean, surveillance apparatuses play an important role in maritime security. It is essential to be added an active, continuous, and extensive monitoring instrument into the existing observation system. High Frequency (HF) Surface Wave Radars is a strong candidate for a ship-monitoring network in wide ocean area. The technique of ship identification with HF radar has been initially established at home and abroad currently, and usually use the automatic identification system (AIS) information to confirm the signal of large targets. However, operational monitoring and major techniques of ship echo signals still need to be improved and optimized. In addition, few studies focus on the performance of ships detection with HF radar. Taiwan has established shore-based HF radar network. This study expects to improve the technique of automatic detection of ships based on the existing methods and assisted by deep learning methods of artificial intelligence. It is beneficial to increase the application value of current HF radar systems and further enhance the effectiveness of ships detection.

The major purpose is to develop and improve the automated ship identification process for quantifying the system surveillance performance via lots of case study. To achieve the above-mentioned research goals. There are three major objectives: The first stage is to establish the quality control process of radar spectrum and AIS data for subsequent comparison and verification. The second stage is dedicated to developing adaptive signal identification (ASI) algorithms and combing with multiple signal classification algorithms (MUSIC) to extract relevant information of ship motion. The final stage is to carry out statistical analysis of a many cases study via the proposed vessel recognition technique and verifying with AIS information.

To ensure the quality of data used in subsequent analysis, this study provided quality control (QA) methods of AIS data and radar spectrum. Regarding the QA of radar spectrum, it mainly integrates the morphology technique and Otsu's method for the Bragg region identification. Accordingly, the region of interest (ROI) can be selected from the radar spectrum for subsequent vessel recognition procedure. In this study, data that has been strongly interfered will be removed, which are affected more than 14% of the spectrum area (outside the Bragg region). The quality control of AIS is based on the received data format and rationality to facilitate subsequent comparison and verification with radar results.

The core work of the second stage is the development of adaptive signal identification (ASI) algorithms. Based on image processing technique and statistical analysis, a set of signal identification methods with rapid execution speed and adaptability threshold can be established with environmental noise changes. The combination of the watershed algorithm extracts the target voltage value from the ASI and input to the multiple signal classification algorithm (MUSIC) for bearing estimation. This study integrates various technique into a set of automatic vessel identification algorithms to facilitate subsequent quantitative analysis. The Kalman filter was used to continuous track the target in the latter procedure. The results show that the Kalman filter can be assisted to predict the target position in the Bragg region and continue to track it until the target sails out of the region.

A suitable deep learning architecture U-Net is selected to extract the features of the first-order Bragg region. The most famous characteristic of this architecture is that a relatively small training set can be used to build a recognition model. In addition, this study also compares the performance of activation functions and optimizers with different combinations in the model: The U-Net model using ELu activation function and Adam optimizer has better prediction performance, with an accuracy rate of over 90% and F1 score over 80%, indicating good accuracy and recall rate; In addition, IoU is even more than 60% (usually more than 50% means that the model has good predictive ability). The results show that the deep learning model can automatically identify the position of the first-order Bragg region under the influence of the strong ionosphere. It is beneficial to improve the selection of the ROI in the vessel signal detection process.

In summary, this study quantified the ship detection performance through long-range HF radar system in the northeast of Taiwan. The proposed algorithm was compared large amounts of radar and AIS information. The statistical results confirm that the HF radar detection rate can reach to 50% with the signal-to-noise (SNR) ratio of the target higher than 17 dB. In addition, large RCS values can be achieved 10 to 40 m^2 when the aspect angle of ship is close to vertical radial relative to the radar station. The results of this research not only enhance the technical capabilities of existing SeaSonde radar, but also prove the system to be used as a response mechanism for early warning systems with long-range.

Key words: high-frequency radar; artificial intelligence; adaptive signal identification; vessel echoes recognition

摘要

1982 年《聯合國海洋法公約》規定各主權國家對於其專屬經濟區(EEZ)，有權享有海洋資源的利用與勘探之特殊權利，同時須肩負起管理和安全之維護，因此掌握即時船舶動態成為各國海洋事務專責單位的主要職責。面對廣闊海域監控之挑戰，整合式的設備能夠各自發揮優勢進而相互彌補，對於海域安全應用相當有助益。其中在遠程監控方面，高頻雷達的超視距特性更是深具潛力之監控儀器，具備主動、近即時，且能克服地球曲率之限制進而擴展偵測範圍。目前國內外雖已初步建立高頻雷達識別船舶回波訊號的技術，並搭配以自動船舶識別系統(AIS)的資訊，確認大型船舶訊號；然而，船舶回波訊號的作業化監控技術之諸多關鍵環節仍存有改進與優化的空間，此外鮮少研究著重在高頻雷達於船舶偵測之效能探討。臺灣現已建立環臺岸基高頻雷達測流網絡，如能以現有的高頻海洋雷達相關技術為基石，進而輔以人工智慧的深度學習方法，來提昇高頻雷達自動偵測船舶技術，將可擴增我國現有的高頻雷達系統的應用價值，並進一步強化高頻雷達用於偵測船舶目標之效能。

本研究目的為強化並研發高頻雷達追蹤船舶回波訊號的自動化技術與流程，並透過大量船舶偵測實例之量化分析，對系統監控船舶性能進行檢討。為達成上述研究目標，本文的主要研究項目有三：第一階段是建立雷達頻譜與 AIS 數據庫之品管技術與流程，確保此二項之資料品質得以應用於後續比對驗證。第二階段是發展船舶自動偵測技術，研發重點是開發調適性訊號識別(ASI)演算法，並結合多重訊號分類演算法(MUSIC)，來提取出船舶運動的相關資訊。最後階段是將發展之船舶偵測技術實際應用於海域船舶之識別與追蹤，且以 AIS 資訊證實後，進行大量實例之統計分析。

第一階段的雷達頻譜與 AIS 數據庫之品管流程主要是為了確保後續分析所使用的資料品質，首先針對雷達品管部分是運用形態學的影像融合處理技術，結合影像二值化分割的處理，進行布拉格區域自動識別，據此可從雷達頻譜中選取布拉格區域以外的範圍作為後續船舶訊號偵測的感興趣區域。本研究以 AIS 資料做為雷達辨識船舶結果的比對及驗證之實況資料(ground truth data)，其正確性是根據接收的數據格式和合理性進行品管。

第二階段的核心工作是調適性訊號識別(ASI)演算法的開發，主要以影像處理技術與統計分析為基礎，建立一套具有執行快速且能夠隨環境雜訊變化而設立調適性門檻的訊號識別方法，並引入分水嶺演算法將目標電壓值訊號從 ASI 中擷取並送入多重訊號分類演算法(MUSIC)進行方位辨識，本研究串連各技術成為一套船舶自動識別演算法以利於後續量化分析。研究後段更加入卡爾曼濾波器進行目標物連續追蹤識別，藉此銜接各段時間的目標物辨識結果，以達到連續追蹤之效，研究結果顯示當目標物進入布拉格區域後，卡爾曼濾波器可協助預測目標物於布拉格區域內之位置，直到目標物航行出該區域後，又可繼續識別與追蹤。

深度學習方法用於提取一階布拉格區域的特徵，選定合適之深度學習架構 U-Net 進行模型之建置，該架構最著名之特點為使用相對較少之訓練集即可建置識別模型，此外文中更比較模型中使用不同組合的激活函數與優化器之表現顯示：採用 ELu 激活函數與 Adam 優化器之 U-Net 模型，具有較佳的預測性能，準確率超過 90%，F1 指數超過 80%，表明其良好的準確率與召回率；此外，IoU 更達 60%(通常 50%以上即代表模型具有良好的預測能力)。研究成果並顯示深度學習模型可於部分強電離層影響下，有效辨識出雷達頻譜中的一階布拉格區域之位置，進而有助於改善前述船舶訊號偵測流程中的感興趣區域之選取。

最後階段，本研究選用位於台灣東北角的長距型高頻雷達為例，將本文介紹之船舶偵測技術之實例分析所偵測出的船舶資訊，以及同時間的 AIS 資料轉換至高頻雷達頻譜上的船舶訊號，經過大量比對驗證，得以量化東北角高頻雷達的船舶偵測效能，經統計分析結果證實當海面目標物訊雜比高於 17 dB 時，高頻雷達偵測率可高達 50%。此外，亦進一步探討船舶姿態與雷達反射截面積(RCS)之關係，當目標物視角接近雷達站徑向垂直角度時，將提供 10-40 m^2 的 RCS。本研究結果不僅增強了現有高頻雷達系統探測和追蹤海上航行船舶的技術能力，更證實了高頻雷達可作為遠程預警系統之潛力。

關鍵字: 高頻雷達，人工智慧，調適性偵測技術，船舶訊號識別

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陳禹儒 謹識

寫于 成功大學

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