

AIN SHAMS UNIVERSITY

FACULTY OF ENGINEERING

Electronics and Communication Engineering Department

Trajectories Classification of two different types of ships

By

MOHAMED FATHI ABDELAAL ELWAKDY

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Under Supervision of

Prof. Dr. Wagdy Rafaat Anis

Electronics & Communication Eng Dept. Faculty of engineering - Ain Shams University

Dr. Mostafa Eltokhy

Electronic Technology Department Faculty of Industrial Education – Helwan University

Dr. Mohsen El-Bendary

Electronic Technology Department Faculty of Industrial Education – Helwan University

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Thesis: PhD in Electrical Engineering (Electronics and Communication

Engineering)

Student Name: Mohamed Fathi Abdelaal Elwakdy

Thesis Title: Trajectories Classification of two different types of ships

Examiners' Committee

Name and Affiliation	Signature
Prof. Wagdy Refaat Anis	•••••
Emeritus Professor	
Electronics and Communications	
Ain Shams University	
Prof. Abdel Halim Abdel Naby Zekry	
Emeritus Professor	
Electronics and Communications	
Ain Shams University	
Prof. Mostafa Sayed AbdelRahman Afifi	
ECE Professor	
Electrical and Computer Engineering	
Modern Academy for Engineering and Technology	

Date: / / 2018

STATEMENT

This dissertation is submitted to Ain Shams University for the degree of PhD of Science in Electrical Engineering (Electronics and Communication Engineering). The work included in this thesis was carried out by the author at the Electronics and Communication Engineering Department, Faculty of Engineering, Ain Shams University, Cairo, Egypt. No part of this thesis was submitted for a degree or a qualification at any other university or institution.

Name: Mohamed Fathi Abdelaal Elwakdy

Signature:

Date: / / 2018

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ABSTRACT

The classification of various trajectories of different objects is an important investigation technique for predicting the kind of the moving objects. In this thesis, object types including fishing boats, tanker ships, Cattle, Deer and Elk are distinguished based on their trajectories and their features. Polynomial functions are used as an efficient tool to extract these features from the segments of the recorded trajectories of the objects under investigation. The features extracted are fed into subtractive clustering procedure to put the data in a group of clusters. then serve as an input to a neural network based identification algorithm.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is used for the classification procedure. The features extracted for all trajectories are represented by groups of membership functions and groups of the Fuzzy If-Then rules. The Initial Fuzzy Inference System (IFIS) is trained using Artificial Neural Network (ANN) by tuning the membership functions to obtain the lowest possible number of hits by the Fuzzy Inference System (FIS) output that misses the targeted object. After training the IFIS we obtain a new system which is called Final Fuzzy Inference System (FFIS).

The Classification of trajectories Algorithm (TCA) is devised for classifying trajectories of two different types of ships: fishing boats and tanker ships. The locations of a tanker ship and a fishing boat are assumed to be collected in the same region without distinction. The performance of the proposed TCA using polynomial functions and ANFIS is tested using different trajectories obtaining highest classification accuracy of 99.5%.

The Developed Classification of trajectories Algorithm (DTCA) is devised for classification of trajectories of dissimilar type like mariner and animal wanderers. The locations are assumed to be collected for all objects in the same unidentified territory. There are two different cases of classification of trajectories: similar and non-similar trajectories. The similar trajectories include only animal trajectories and non-similar trajectories include mariner trajectories. The similar trajectories of combinations of two animals are classified in pairs to get highest classification accuracy of 98.83%, while the non-similar trajectories of ships are classified against the animal trajectories to get highest classification accuracy of 99.11% by using ANFIS. The performance of DTCA is tested by using different trajectories of combinations of object pairs.

The Advanced Classification of trajectories Algorithm (ATCA) is further proposed to classify the trajectories of different objects. The Three-fold Cross

Validation Technique is applied to the datasets available where they get divided into 3 sets for optimized training and detection. The similar trajectories of each two objects are classified to get the highest classification accuracy of 97.29%. The non-similar trajectories are classified versus similar trajectories to get the highest classification accuracy of 95.30%. The performance of ATCA is tested using different trajectories of all kinds of investigated objects. The proposed algorithm results are compared to the Support Vector Machine (SVM) which was developed by other researchers as baseline for our results. The results of our proposed algorithm ACTA outperform the SVM baseline results in terms of accuracy.

Keywords- Subtractive Clustering; ANFIS; Classification of trajectories Algorithm (TCA), Developed Classification of trajectories Algorithm (DTCA), Advanced Classification of trajectories Algorithm (ATCA)



Monday, 23 January 2017

RE: Mohamed Elwakdy

To Whom It May Concern

This letter is to confirm that the Advanced Algorithm for Trajectories Classification of Different Objects developed by Mohamed Elwakdy could have significant commercial benefit. Currently we are in discussions with one of the government appointed Accelerators who may be interested in co-funding it with a commercial entity already operating in relevant industries.

If they proceeded this we believe could provide a potentially significant benefit to New Zealand, through both recognition on the broader world stage and generation of employment to further develop the algorithm in to commercial products.

Kind Regards

Michael Masterson

Global Head of Commercial - +64 21 703999

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