A NOVEL POTENTIAL FIELD ALGORITHM AND AN INTELLIGENT MULTI-CLASSIFIER FOR THE AUTOMATED CONTROL AND GUIDANCE SYSTEM (ACOS)

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Abstract: The ACOS project seeks to improve and develop novel robot guidance and control systems integrating Novel Potential Field autonomous navigation techniques, multi-classifier design with direct hardware implementation. The project development brings together a number of complementary technologies to form an overall enhanced system. The work is aimed at guidance and collision avoidance control systems for applications in air, land and water based vehicles for passengers and freight. Specifically, the paper addresses the generic nature of the previously presented novel Potential Field Algorithm based on the combination of the associated rule based mathematical algorithm and the concept of potential field. The generic nature of the algorithm allows it to be efficient, not only when applied to multi-autonomous robots, but also when applied to collision avoidance between a single autonomous agent and an obstacle displaying random velocity. In addition, the mathematical complexity, which is inherent when a large number of autonomous vehicles and dynamic obstacles are present, is reduced via the incorporation of an intelligent weightless multi-classifier system which is also presented.

1 INTRODUCTION

This paper presents additional novel algorithms, methods and technologies adapted by the ACOS automated guidance system (Statheros, 2006) for collision free autonomous navigation, not only in a single autonomous manner, as initially presented in (Statheros et. al., 2006), but also for multi-autonomous vehicles in the presence of independent dynamic obstacles.. The technologies employed fall into three major categories: Novel Potential Field autonomous navigation techniques, multi-classifier design and direct hardware implementation. This paper presents an overview, further development and ideas regarding the integration of these technologies within the ACOS system. The paper presents the novel features of the Potential Field methodology described in (Statheros 2007), and also the new concept of Trajectory Equilibrium State (TES) between a potential field autonomous vehicle and a dynamic obstacle. In addition, we propose the combination of the multi-classifier with the novel potential field algorithm in a new hybrid navigation system. This is followed by a description of the multi-classifier framework employed by ACOS which utilises weightless neural network technology allowing a rapid adaptable learning environment and facilitating efficient direct hardware implementation. The multi-classifier additionally possesses the desirable properties of 1) a capacity to implicitly adapt to the relative discriminant abilities of its component classifiers and 2) be able to accept both absolute and probability based classifications from its component classifiers.

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2 NOVEL POTENTIAL FIELD METHOD FOR MULTI-AUTONOMOUS VEHICLE NAVIGATION

A major part of ACOS work for autonomous navigation is based on novel potential field algorithmic methodology improving both single and multi-autonomous vehicle navigation (Statheros 2007). The generic concept of “artificial potential fields” originates from (Khatib, 1985). This study introduces the potential field method (PFM) for real-time obstacle avoidance for both manipulators and mobile robots. In later years PFM quickly gained popularity for autonomous vehicle navigation because of its elegance and simplicity. A Widely used PFM for mobile robot real-time obstacle avoidance is termed Virtual Force Field (VFF) (Borenstein, 1989, 1990). The VFF method has also been utilised in complex hybrid systems for air, land and water based autonomous navigation. A number of VFF algorithms specialised in water based navigation are briefly explained in (Statheros, 2008).

However, Artificial potential field based algorithms experience local minima traps, which cause autonomous vehicle’s trajectory deadlocks and/or oscillations (Koren 1991). This problem can be resolved by PFM in integration with intelligent methods and/or mathematical navigational algorithms.

In recent years potential field algorithms have also gained popularity in the field of multi-autonomous navigation (Pradhan 2006, Masoud 2007). In (Statheros 2007) a novel multi-autonomous navigation algorithm enables a simple VFF algorithm to navigate local multi-autonomous independent vehicles exceptionally efficient in terms of trajectory length, trajectory smoothness and time of arrival. This approach uses a novel rule-based mathematical algorithm and the newly defined concept of trajectory equilibrium state (TES).

2.1 VFF Trajectory Equilibrium State

In a multi-mobile robot environment where the robots are guided by the VFF method, in which the virtual repulsive force is described in (Statheros 2007), we can observe the Trajectory Equilibrium State (TES) as shown in Figure 1. Here, we observe that the robot trajectories cross at point C to reach their target destinations in straight line trajectories. However, with VFF, the trajectory diversion leads to autonomous navigational deadlock and both robots stop at points D and E without reaching their target destinations T1 and T2. We can define the distance DE as $D_{Saturation}$, the minimum distance they may have between them. The robots will only stop without reaching their target destination in Absolute TES. Where equation (2) is not fully satisfied but equation (1) is satisfied, we define the state as Close TES.

$$D_{Saturation} \le D < D_{Efficiency} \qquad (1)$$

$$AC = BC \text{ and } V_1 = V_2 \qquad (2)$$

In equation 1, $D_{Efficiency}$ is the minimum distance between the two robots so the non-linear effect of the equation 1 is not apparent. Where V1 is the speed of mobile robot 1 and V2 is the speed of mobile robot 2.

As stated above, the TES causes trajectory inefficiencies such as long and curved power consuming trajectories for all the guided robots. In the most extreme case, absolute TES, both robots divert from their target destination and the distance between them decreases to the point where the resultant force vectors are equal to zero. The Absolute TES has been identified utilizing two mobile robots in (Statheros 2007).

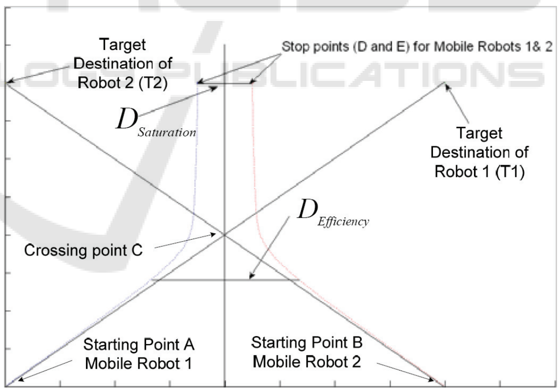

Figure 1: Two mobile robots at Absolute Trajectory Equilibrium State (TES).

2.2 TES Detection and Avoidance

The TES detection and avoidance algorithm predicts and prevents Absolute and Close TES. This algorithm maintains close to straight line efficient trajectories for the robots in cases of possible collision by adjusting separately their speeds. The performance of this algorithm is demonstrated in Figure 2.

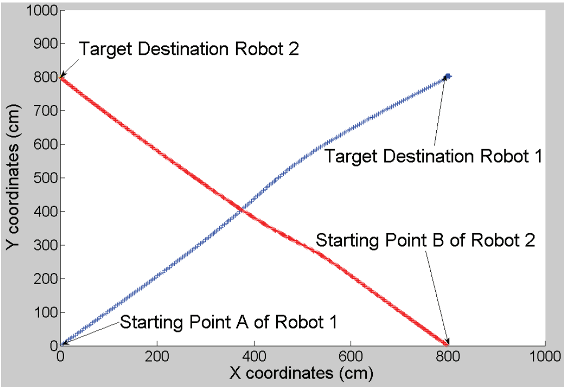

Figure 2: Two mobile robots close-optimum trajectories due to TES Detection and Avoidance algorithm in case of Absolute TES.

The above has introduced the concept of guiding independently multi-autonomous robots or vehicles with identical algorithmic principle with exceptional efficiency. However, in this paper, we have identified that the above algorithm is more generic in nature, as it may also be applied to dynamic obstacles. For example, in Figure 3, a collision scenario is presented between a dynamic obstacle and a standard potential field guided robot. In this case, we can consider a new concept of TES between a potential field robot and a dynamic obstacle. This TES forces the potential field guided robot to divert from its target destination and follow the inefficient trajectory shown in figure 3. The TES detection and avoidance algorithm can also be applied in this case. The algorithm incorporates a velocity variation of the autonomous guided robot based on the potential field algorithm dynamics. The effectiveness of the algorithm is displayed in Figure 4, where the autonomous vehicle follows a near optimum straight line trajectory.

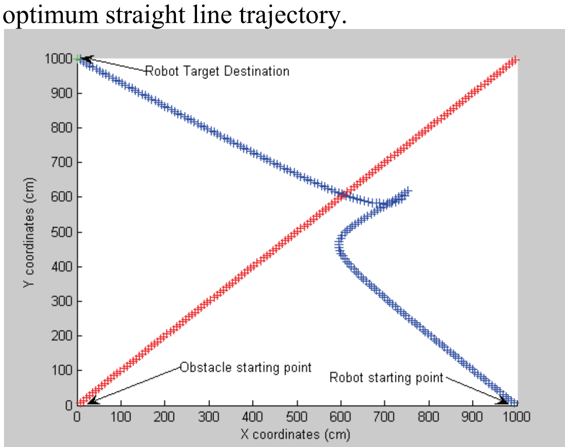

Figure 3: Standard Potential Field robot with dynamic obstacle.

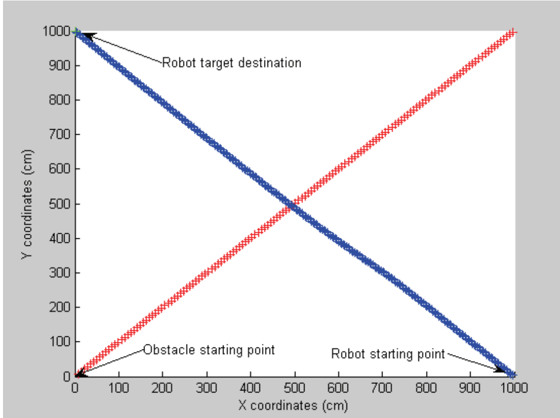

Figure 4: The effect of TES Detection and Avoidance algorithm when a Potential Field robot is in TES with a dynamic obstacle.

The processing requirements of the above algorithm increase in a presence of a large number of autonomous vehicles and/or dynamic obstacles. We can reduce its processing load by focusing the algorithm onto a group of similarly behaving dynamic vehicles and/or obstacles that are recognised by an intelligent multi-classifier, which we present in the next section. This is possible due to the patterns of location, direction, speed and potential field algorithm dynamics, which are generated from the autonomous vehicles and/or dynamic obstacle in the same local navigation environment).

3 THE INTELLIGENT FAST-LEARNING MULTI-CLASSIFIER SYSTEM

Modern intelligent Robotic Guidance systems are being employed in practical application domains where the required performance level often exceeds that achievable from a single guidance paradigm typically because the complexity of the problem is such that too many potential outcomes are present, equivalent to the number of pattern classes when the system is viewed as a pattern recognition problem. To address this issue, current systems often concurrently employ a number of distinct classifiers, where the component classifiers are trained on a subset of situation which the robotic system may encounter in practice. Therefore, the component classifiers will possess the ability to distinguish well between certain situations but will be unable to offer the same distinguishing pattern classification performance over the entire range of scenarios specific to the problem domain because they are unaware of all possible situations. In such circumstances, engineering a solution to a practical problem is reduced to a selection process of available classifiers where the combination of the classifiers chosen is able to distinguish the entire set of pattern classes present within the problem domain. A combiner classifier is required in addition which is trained on the outputs of the component, or base, classifiers and makes an overall decision.

The ACOS system utilises an intelligent multi-classifier combiner system which is able to automatically assimilate outputs of component system classifiers which are inaccurate due to their restricted training knowledge and produce a single classification for a given classification instance The system possesses the following significant properties:-

- All base classifiers and the combiner classifier follow a generic architecture based on the Probabilistic Convergent Network (PCN) (Howells 2000, Lorrentz 2007).
- The significance of the classification decision of a given classifier is varied according to the likely pattern classes under consideration. Therefore, a classifier which possesses good knowledge of the scenario in question is able to provide a strong weighted decision which is utilised by the combiner network. Conversely, when an unfamiliar scenario is encountered, a low weighted incorrect decision is produced due to the unfamiliarity of the classifier with the true scenario.
- The multi-classifier system possesses fast learning properties so that the significance of class distinguishing properties are immediately accepted by the system
- The system is problem domain independent and may be adapted to a large number of automated navigation based scenarios.
- The system uses simple logic operations to guide its decision making process and it is thus suitable for fast direct hardware based implementation

As stated, the proposed technique employs a type of weightless artificial neural system known as the Probabilistic Convergent Network (PCN) to assimilate the classification potential of each of the component classifiers employed in a given situation. The PCN network architecture (Howells 2000, Lorrentz 2007). is designed to provide an extended recognition information base to the user whilst retaining the training and performance potential achieved with previous Weightless architectures (Austin 1998). An example PCN architecture is illustrated in Figure 5.

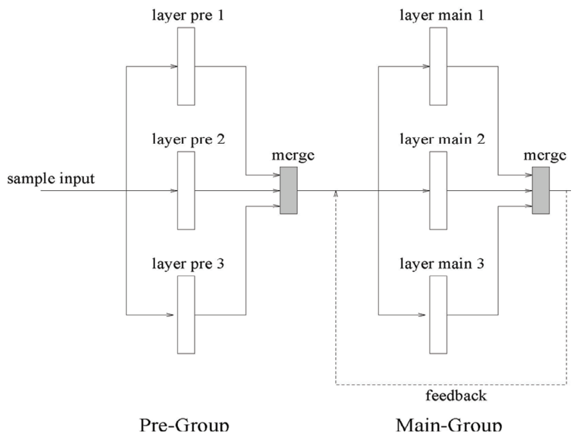

Figure 5: PCN Network Architecture.

The following are significant points regarding the architecture:-

- The neurons comprising the network are arranged in $x \times y$ matrices or layers where x and y are the dimensions of the input sensor data under consideration.
- Each element within the sensor data is therefore associated with a corresponding neuron within each layer.
- The layers comprising the network are arranged in two groups, termed the *Pre* group and the *Main* group. A *Merge* layer exists after each group whose function is to combine the outputs of the constituent layers of the group. The connectivity of the neurons comprising a *Merge* layer is equal to the number of layers within the group to which it pertains.
- The merged output of the *Main* Group is fed back, unmodified, to the inputs of each layer comprising the group.
- The number of layers within each group may be varied depending on the recognition performance required from the network.
- The constituent layers of a group differ in the selection of sensor data elements attached to the inputs of their constituent neurons (termed the *connectivity pattern*).

- Neurons within a given layer possess the same connectivity pattern relative to their position within the matrix.

The PCN architecture utilises highly efficient training and recognition algorithms which are detailed in (Lorrentz 2007). These allow the network to produce weighted decisions on their output giving a confidence level associated with the decision. Specifically:-

- Symbols within the PCN architecture are taken from an extended *compound* set.
- A given symbol is designed to contain a component for each of the possible pattern classes on which the network has been trained.
- Each component itself is constructed from a pre-determined number of sub-symbols. This number represents the number of *divisions* available for each pattern class where each divisional symbol represents a probability approximation that the given sample pattern belongs to the given pattern class.

The neurons comprising the network differ between the *Pre* and *Main* groups. The *Pre* group neurons take their inputs from the binary sensor values comprising the network input data. The contents of the memory locations of the neurons are taken from the extended compound set of symbols described above. The main group neurons take their inputs and memory contents from the compound set of symbols.

Due to the weightless nature of PCN it lends itself to straightforward hardware implementation that requires mainly standard memory to realise the network structure and some limited arithmetic resources. An enhanced version of the PCN architecture has been prototyped and forms a hardware fabric the for the systems implementation (Lorrentz 2008).

The ACOS system consists of several base PCN base classifiers based on separate scenarios which a robot may encounter. It is infeasible to train a single PCN classifier with a large number of scenarios due to the exponential increase in memory required as each neuron memory will increase in size for each new scenario. The PCN architecture naturally lends itself to employment as an intelligent multi-classifier however. To achieve this end, the output classifications of the selection of base classifiers employed, form the input to a given combiner PCN classifier. The outputs of the combiner PCN will then represent a weighed classification for the problem at hand based on the combined wisdom of the component classifiers as illustrated in Figure 6.

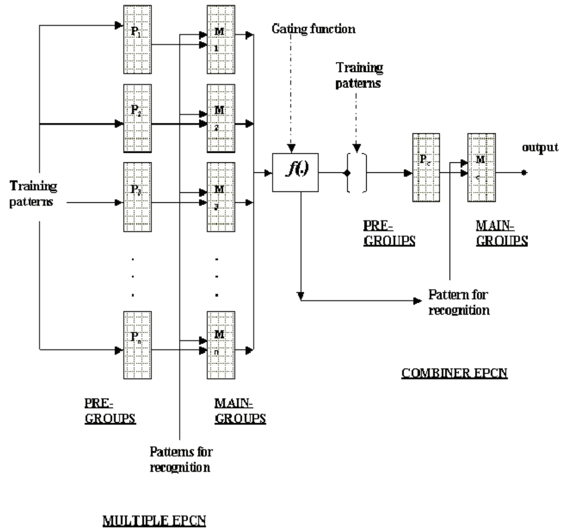

Figure 6: Schematic of the PCN based Multi-Classifier.

As stated, in order to employ the PCN architecture as a basis for a multi-classifier system, it is necessary to combine the outputs of the component classifiers to form a single input which may be considered as a classification image for the particular problem in question. The general strategy requires the following steps to be taken:-

- Outputs of component classifiers are interpreted as binary numbers, either indicting a single preferred pattern class or representing a combination of classed with associated probabilities.
- The combiner PCN overloads the meanings of the outputs of the component classifier in order to address the memory scale issue associated with the requirement that it be able to distinguish between a large number of component decisions. So, for example, the meaning of class decision 1 for base classifier 1 will differ from the same output for classifier 2. However, the combiner PCN sees a compound input pattern which essentially represents a compressed representation of all possible decision scenarios with associated weightings and is able to efficiently reach a conclusion.
- Suitable training examples must be compiled which will allow the PCN system to distinguish between the various scenarios. To this effect it is a supervised learning environment.

Examples of classifications may now be

presented to the PCN architecture according to the training algorithm in (Howells 2000, Lorrentz 2007). The system effectively relies of the fact that if a base classifier encounters a situation with which it is familiar (i.e. it has encountered in training), it will produce a decision with high confidence. Conversely, if a base classifier encounters a scenario with which it is not familiar, it will produce a classification from one of the scenarios which it is familiar but with low confidence. i.e. it will produce an erroneous but low weighted result. The combiner PCN is able to sift these decisions and produce the desired decisions based on their confidence rating.

4 CONCLUSIONS

The ACOS project has been successful in producing an integrated, automated, robotic guidance system which is highly flexible and capable of fast autonomous learning. It has achieved its primary aim of providing state-of-the-art knowledge on autonomous navigation techniques and technologies as well as a novel autonomous navigation techniques architecture which constitutes design and implementation suitable for industrial exploitation.

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