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Movement Persuit Control of an Offshore Automated Platform via a RAM-based Neural Network

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***Abstract*—The reproduction of the movements of a ship by automated platforms, without the use of sensors providing exact data related to the numeric variables involved, is a non-trivial matter. The creation of an artificial vision system that can follow the cadence of said ship, in six axes of freedom, is the goal of this research. Considering that a real time response is a requisite in this case, it was decided to adopt a Boolean artificial neural network system that could identify and follow arbitrary interest points that could define, as a group, a model of the movement of an observed vessel. This paper describes the development of a prototype based on the Boolean perceptron model WiSARD (Wilkie, Stonham and Aleksander's Recognition Device), that is being implemented in the C programming language on a desktop computer using a regular webcam as input.**

***Keywords*—Stewart platform, weightless neural networks, WiSARD.**

I. Introduction

Indubitably, one of the main sectors of commercial activity is transportation and, consequently, there is a trend to improve all aspects of this sector. One of the industries presenting the most evolution in the development of new technologies is the naval industry, upon which a great deal of the world economy depends on. The advantages of using ships for transport, specifically containers, are even more numerous when it is observed that several regions of the world possess the logistics and infra-structure necessary to support it. Over 150 countries are prepared to receive container ships, making it a wise choice when considering options for the massive transportation of products. Consequently, the naval industry has invested time and money to design and build larger and faster ships with the intention of generating a greater flow of products and reducing operation costs.

Unfortunately, all those improvements aren't available everywhere. Due to port size and access restrictions (either too small or too shallow), more advanced and lager ships aren't able to stop at many of the aforementioned countries. Such problems lead to the creation of a new scenario, specifically in offshore cargo transfer. Under the new circumstances, the loading and unloading of container ships in areas around the ports are allowed through the means of an auxiliary ship doted with a robotic container crane.

The Stewart platform is a robot with a parallel architecture that moves in six axes of freedom, characteristics that are suitable to replicate the movements of a ship [1]. The main goal of this project is to create an artificial vision system capable of following the cadence of a target ship, in order to reproduce those movements with a Stewart platform (Figure 1) [2].

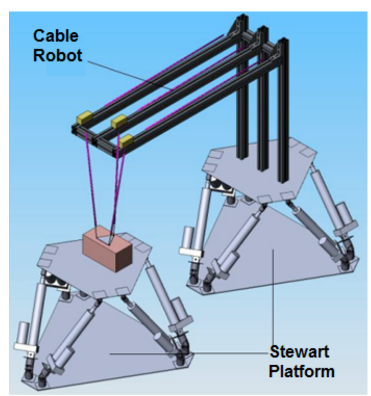

Figure 1. General Design of Cable Robot Platform [2].

Considering that a real time response is an important requisite, the **WiSARD** (Wilkie, Stonham and Aleksander's Recognition Device) [3] RAM-based artificial neural network model is adopted in order to identify and follow interest points that could, as a group, define a geometric model of the observed vessel's motion. This paper presents the design and

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implementation, on a standard desktop computer using a regular webcam for input images, of a prototype capable of real time training and movement persuit of interest points.

The following is how the remainder of this paper is organized. Section II deals with the importance and issues involved in offshore loading and unloading. The **WiSARD** Boolean perceptron is explained in Section III. Section IV presents the design and implementation of our "weightless" artificial neural network based vision system dedicated to movement persuit. Section V contains our conclusions, ongoing and future work.

II. Offshore cargo handling

Port cargo handling operations are realized daily in order to load and unload commercial ships, the main means of transportation of various types of products around the world. In such operations, a very relevant issue is the reduction of accident risks. On the other hand, reducing the time of port cargo handling operations is a way of reducing costs and is a goal to be achieved through the constant technological development of equipment (cranes). Currently, specialized container cranes and conventional cranes are used in ports to load and unload containers to/from ships [4] [5] [6].

A crane equipment consists of, basically, an operation cabin, an articulated jib, and vertical cables supporting the hook securing the load, in order to perform the lifting and lowering of the container to an appropriate local. Although of widespread application, cranes are machines that do not have the capacity to guide the pendulum cargo in precise way since its mechanical configuration makes the movement in a desirable orientation difficult. There are ships that are equipped with automated cranes (accelerometers, gyroscopes, positioning sensors, etc) with the only purpose of providing a rapid cargo transfer (loading or unloading) (Figure 2) [7]. Current technology facilitates the operation and control of cranes, but still restricted to the experience of the human operators who, in most cases, are qualified and trained for different working conditions, thus restricting the ability of performing a safe cargo handling operation at sea.

Figure 2. Offshore Loading and Unloading Transfer Simulation [7].

Cable-suspended manipulators, also known as cable-driven robots or tendon-driven robots, have been investigated as agile alternatives and prototypes have been already developed [8] [9] [10] [11] [12]. Such systems have been designed to perform cargo transportation and applied in conventional manufacturing process automation. Cable-suspended manipulators have been considered as a new technology in the design and implementation of container cranes, since it makes easy to obtain positioning and orientation information about their effectors [13] [14] [15]. As their main functions are elevation and positioning of objects or tools, consequently one can easily perform cutting operations, excavation, painting, welding, etc.

The motivation for the construction this structure came from the need to make the assembly of heavy loads in shipyard, civil construction, and various industries that are characterized by the existence of highly dangerous jobs for workers during the handling of objects. Thus, a cable-suspended manipulator can act replacing cranes, which are devices that do not have the ability to guide the object being loaded, and did not have efficient control of oscillatory movements.

The present work is in the context of a project that aims at the design and implementation of a cargo transfer automated system for use in offshore systems at risk of heel and systems that could not dock at small ports [16]. This system, when matured and applied to the shipping industry, may turn economically viable, for instance, the unloading of few items (e.g., containers) from ships carrying large quantities of containers. Such system has the potential of (i) allowing a great reduction in maintenance costs of large capacity ports, and (ii) facilitating rescue of cargo and people at risk.

More specifically, the scenario that will be assumed in this research is the one in which one could not count with positioning sensors in order to provide a precise control of a crane performing an offshore cargo transference. Therefore, an artificial vision system, that could count with one or more cameras, in order to follow the movements, in real time and in six axes of freedom, of a target ship. The adoption of a Boolean artificial neural network model is justified by the aforementioned requisites, so that real time training and recognition could be easily achieved.

A possible operational scenario of our artificial vision system would be the one following: (i) an operator would chose particularly representative points of interest over the deck of the ship to be approached and teach them, through training, to the artificial vision system; (ii) a geometric model of the target ship deck would be built taken the chosen (and trained) interest points into account; (iii) the real time images of the target ship would fed our artificial vision system so that the interest points would be followed in real time, so the geometric model of the ship could serve as a positioning reference to the automated crane. The following presents the Boolean artificial neural network model adopted.

III. WiSARD: a Weightless Neural Network

McCullloch&Pitts' paradigmatic artificial neuron is based on the synaptic strength, i.e., synaptic weights, found in the biological neuron [17]. Alternatively, in the **WiSARD** (**Wi**lkie, **S**tonham and **A**leksander's **R**ecognition **D**evice) Boolean perceptron, the connectivity pattern between axons and dendrites, i.e., the dendritic tree topology, a quite noticeable morphological feature of biological neurons, is central to the model [3] [18] [19] [20]. More precisely, a neuron's dendritic tree receiving excitatory and inhibitory inputs from n neighbouring neurons is captured by the functionality of a n bits address RAM (*Random Access Memory*). As illustrated by Figure 3, each RAM-based neuron is capable of recognizing n bits (n-tuple) inputs coming from a target pattern.

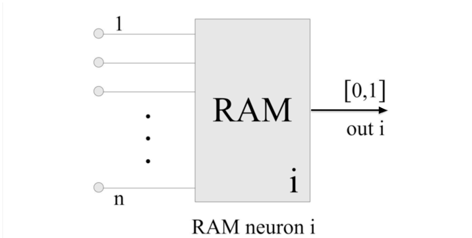

Figure 3. A WiSARD's RAM-based neuron.

Training is performed in the following way: (i) all RAM neurons are initialized with "0"s in all of its contents; upon presentation of a (binary) training pattern, the contents of the specific RAM location addressed by the n-tuple are set to "1". Although standing alone RAM neurons are efficient in pattern training and recognition phases, generalization is a missing capability since only previously presented patterns can be recognized. In order to overcome this drawback, RAM neurons are organized in the so called *discriminator* structure, illustrated in Figure 4, so that each and every RAM neuron, of a total of N neurons, learn and recognize a sub-set of a $n \times N$ input pattern [21] [22]. This way, a discriminator is capable of recognizing a possibly unseen input pattern X by adding all RAM neurons outputs.

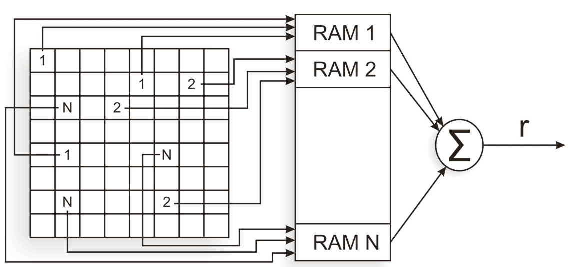

Figure 4. WiSARD discriminator.

Figure 5 illustrates the structure of a *multidiscriminator* **WiSARD** perceptron: a set of m discriminators, each one representing a different pattern class. An input pattern X is, after passing through a shuffling function E, submitted to: (i) a specific discriminator, during training phase, and to; (ii) all discriminators, during recognition phase, when all m responses are compared and, considering a *confidence* level d, a winner response is produced.

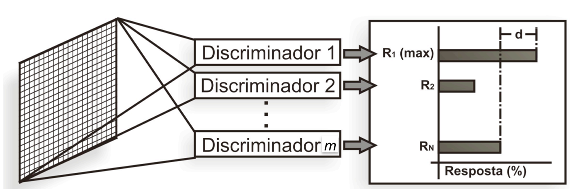

Figure 5. A multidiscriminator WiSARD perceptron.

IV. Motion Capture of a Vessel

In this section we shall describe the proposed function of the artificial vision system responsible for the capture and pursuit of the vessel's deck movements.

A. *General description*

Initially, the image of the vessel that will be observed is captured. This capture can be performed by one or more cameras. After that, the reference points that will provide a geometrical description of the vessel's deck are chosen. Based on the location of the reference points, each one dynamically found by a **WiSARD** percetron, the movements are calculated and reproduced by the Stewart platform.

B. *Visual positioning recognition*

In order to follow the reference points, a **WiSARD** network is trained using the image of one of such points, that is framed in the input image. The initial localization of a reference point in the image (e.g., starting from the position illustrated by Figure 6.a) is accomplished by performing a window scan, under the recognition phase of the **WiSARD** network, around the entire image [23]. The point with the greatest response is selected, as shown in Figure 6.b. Because this process can be computationally expensive, a smaller **WiSARD** network is used. It represents the same input image of the reference point but with half of its original resolution. Following the use of the reduced image, the points with the highest scores are then checked again in full resolution. Thus, greatly reducing the search time, in approximately 16 times, making its use viable in real time.

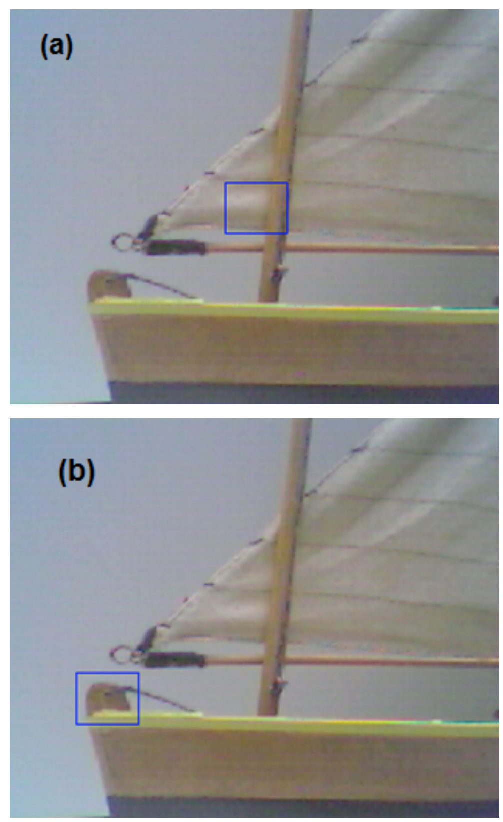

Figure 6. Persuit of bow: (a) Initial state ; (b) Final state

C. *Current state of the WiSARD recognition system*

The visual recognition process begins by treating the input image. First, a colored image is obtained (Figure 7.a; in the present case, due to restrictions imposed by the camera, its resolution is 352 x 288 pixels) defined by the RGB system (the information contained in each pixel consists in the tones of red green and blue present in each one). Using this image, another is created by applying a filter to change it to grayscale (Figure 7.b). After that, another filter is applied and this last image consists of only black and white dots, called a binary image (Figure 7.c). Both filters are from the OpenCV library, open source and available at [24].

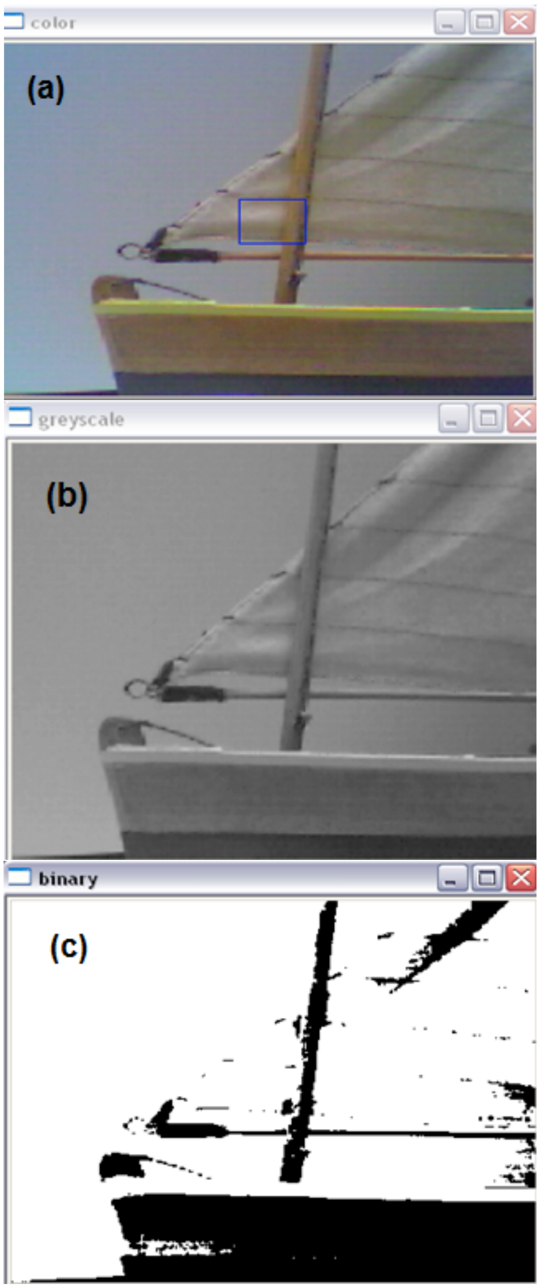

Figure 7. Examples of each type of image generated (a) Color; (b) Grayscale; (c) Binary

The binary image is used as input for the **WiSARD** network, considering that it can be easily represented as a string of “0”s and “1”s. This is the image in which the reference points are searched for. The training and search for reference points is performed using an area of the image limited by a frame, containing 44 x 36 pixels, illustrated in blue in Figure 6 (a).

In order to perform the persuit the entire image is searched for the reference point, utilizing the method described earlier, with a **WiSARD** network that corresponds to an image with a smaller resolution. Following that, the procedure is repeated continuously, but in a smaller scale. This way, the reference point is searched for in a 50 pixel radius of where the point was found before.

Figure 8 illustrates the process by which the pitch angle of a vessel could be calculated, by using two reference points; one at the bow and another at the stern. Consider that both points were found by two different **WiSARD** networks fed by two different cameras, but with the same referential. In order to track the movements of the other axes, more reference points must be trained, always favoring the geometric representation of the surface of the deck. These relative geometric positions will feed the controller of the Stewart platform with the movements it shall execute. However, the definition of an operational form for the selection of the reference points that could possibly be defined online by a trained operator isn’t being considered for this paper.

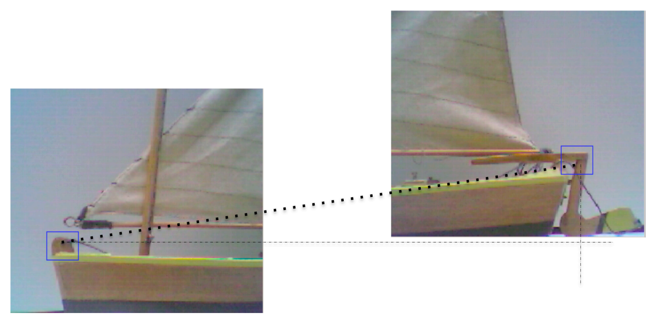

Figure 8. Capture of the pitch angle.

V. CONCLUSION AND FUTURE WORK

A novel application of the WiSARD weightless perceptron in the capture of a vessel’s movements was presented. The role of such artificial vision system lies in the context of allowing safe offshore cargo handling via the use of an automated cable-suspended manipulator. A proof-of-concept was produced in the form of an artificial vision system capable of real time training and recognition of a singe arbitrary reference point of a ship’s deck. It is worth noticing that our implementation was made in an out-of-shelve desktop computer using a standard webcam. Preliminary tests indicates that more interest points can be easily handled by a single desktop computer, suggesting that the potential of our approach was still not reached.

Although the classical multilayer perceptron (MLP) can be considered computationally equivalent to the WiSARD perceptron [11][12], it could not fulfill the real time requisites involved in our context, especially when taking the training phase into account.

Operational aspects related to the choice of reference points is an issue that deserves further attention and must be tackled in the near future. The Stewart Platform to represent the transfer ship is being simulated in a virtual environment. Meanwhile, the design of a cable-suspended manipulator is about to be tested through the construction of a small-scale prototype. The development of calibration routines and the integration of computational and mechanical parts should be facilitated through this approach.

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