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A New System for Angular Velocity Estimation for a First-Order Manipulator Using Artificial Intelligence and Sliding Mode Differentiator

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Abstract: On a NVIDIA Jetson Nano device, this study illustrates a unique and original usage of automated control and artificial intelligence algorithms for angular velocity estimates of a first-order manipulator device. A platform can be used as a position estimation platform using computer vision and three state estimation algorithms: sliding mode differentiator, high gain observer, and static filter. A hybrid system for process performance improvement is proposed using computer vision and three state estimation algorithms: sliding mode differentiator, high gain observer, and static filter. The results of numerical simulations are provided, as well as real-time judgments. The ITAE and IAE indices reveal that the sliding mode differentiator is much superior in angular velocity estimation for position signals utilizing artificial intelligence sensors.

Keywords: Artificial vision, NVIDIA Jetson Nano, Sliding modes, Estimation, High gain.

1. INTRODUCTION

The study of motion, which refers to the change in the location of a particle or a system of particles with respect to time, is called mechanics. This system of particles, together with their motion, is called a mechanical system. As previously stated, a mechanical system is a collection of parts that transport or change energy (Cosenza et al. 2015). All robotic systems are mechanical systems first and foremost, which leads to mathematical modelling based on Newton's law dynamics, as well as electrical and computer design. To manage these systems, one must modify their natural dynamics in such a manner that they have a desired reference point. The design of manipulator robots, in which visual, referenced, and resilient dynamics are desirable, is a classic example of the former. The extension of controlled manipulator robots has gained a lot of attention in recent years because it is well known that automation is a technical boundary issue in the latest generation of industrial technologies. The utilization of fourth generation technology, which focuses on robotics mixed with artificial intelligence techniques and the most powerful electronics, is now being advocated. The notion of applying artificial intelligence approaches to electromechanical systems or robots has been around for decades, and fuzzy logic was one of the most quickly adopted ideas. Modern control theory already includes fuzzy logic control. Samir Kouro and Rodrigo Musalem developed a control using fuzzy logic to control a helicopter prototype in 2002. By its nature, a helicopter's stability control can be thought of as an inverted pendulum with two actuators in which they describe the system's process and characteristics, in this case using an optical sensor to determine its inclination (also known as an encoder) (Kouro & Musalem, 2002). The real-time estimation methods such as the high gain observer, static low-pass filter, and Super Twisting estimator are programmed on an Arduino UNO-MATLAB platform.

In 2021, David Fernández Llorca, Antonio Hernández Martínez and Iván García Daza develop a paper about speed estimation using artificial vision, which is called “Vision-based vehicle speed estimation: A survey”. They explain different algorithms of distance and speed of a vehicle described in more than 135 and propose a method using vehicle detection, position determination and physics equations for determinate speed and distance traveled. (Fernandez-Llorca et al 2021).

A simulation of an inverted pendulum control system, which is the foundation of any robotic manipulation system, was carried out by Valenzuela-Hernández et al in 2013, with the goal of designing a robust control approach based on artificial intelligence. One of the advantages of using an artificial intelligence-based control system is that it does not require a rigorous mathematical model of the plant; however, one of the complexities is that the effectiveness of this control system is directly dependent on the knowledge of the expert who describes the system's dynamics using linguistic sentences (Kouro & Musalem, 2002). It has been possible to investigate the design of robust controllers and compare them to classical techniques, such as the traditional PD and PID control with the most modern Mode Control (SMC) for manipulator systems but with the provision of all states to measure in work such as (Nasis et al 2012). However, this is not always possible, and it is also sometimes necessary to use non-invasive techniques where machine vision plays an important role, such as using artificial vs. natural vision. (Rodriguez-Rangel et al 2022).

Complex approaches based on state observers or the renowned Kalman filter must be employed to estimate the speed using artificial vision techniques, with which a system with memory may estimate the speed based on a fixed reference point based on past information. This type of technique, which is based on feedbacks and derivative solutions, has issues in the presence of analog noise. Furthermore, the estimation must be calculated for each pixel of the general matrix of the camera sensor, making it a very difficult problem to calculate for high resolution rates. Estimation techniques based on neural networks have been implemented, but they must be trained on a large database, which is not always practical. Also, because the learning algorithms are based on the calculation of immediate derivatives, they will have problems with singularities in the process of identification and learning for the calculation of the network's weight matrices (Rodriguez-Rangel et al 2022).

Therefore, it is necessary to search for a technique that is robust to analog noise, easy to implement, with low computational cost, that also allows us to measure the position based on artificial vision algorithms, but that estimates the immediate angular velocity in real time in a way that is insensitive to disturbances. In this work we propose a real-time estimation system based on the interconnection of two apparently very dispersed systems: an estimator based on sliding mode control techniques and real-time computer vision for comparison with classical techniques. An NVIDIA Jetson Nano platform interfaced with an Arduino - MATLAB system will be used to test and validate the algorithms proposed in this work.

2. MATHEMATICAL MODELING AND PROBLEM DEFINITION

A simple pendulum is a mechanical system with a mass hung by a rope or any other minimal fixed element that allows it to produce oscillatory motions by applying forces, as shown in Figure 1, and this mechanical device is the fundamental system of a manipulator robot by definition. Because it is the most basic component of a robot, it has been widely researched over the past century. It was able to acquire many kinds of control system, as well as estimation and optimization of the device's dynamics. When a force is given to the pendulum, it will move, but the continual action of gravity pressing on it will gradually lead it to remain vertically still, making it a stable dynamic system since it will always tend to return to the origin (Kahalil, 2002).

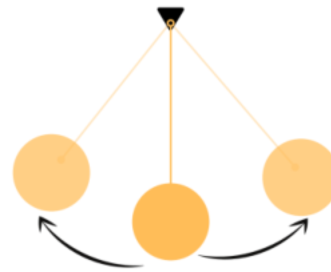

Figure 1. Simple pendulum dynamic.

However, the second equilibrium point is unstable. A mass is supported by a pole and connected to a motor in an inverted pendulum system. The motor's movement or torque leads it to stabilize at a reference point, most typically a vertical, producing a desirable angle or angular dynamics and so achieving the intended trajectory. This indicates that it is a nonlinear system with a level of complexity that has piqued academic interest in experimenting with, evaluating, and comparing contemporary control strategies. The fixed inverted pendulum system (Messner et al., 2017) has been activated as a result of all this (Ooi, 2003). We will focus on the mathematical model of the static pendulum in this study, reaffirming that this is the simplest robotic manipulator device par excellence and that by doing so, we will be able to expand the outcomes of this research effort to far more sophisticated devices in the future. The robotic device's model is as follows (Vidyasagar et al. 1994):

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = -\frac{g}{l}\sin x_1 - \frac{k}{m} + \frac{1}{ml^2}u(t) \tag{1}$$

Where g(x) and f(x) are bounded, differentially continuous, and Lipschtz functions, respectively. For any f, g>0, such that $|g(x)| < g$ and $|f(x)| < f$.

To control or regulate the preceding system, it is important to be able to estimate all of the states, that is, to estimate all of the states through a signal, either a position or velocity signal, since the classical or modern controllers. As a result, the key issue is being able to predict velocity signals from location inputs. This research focuses on the robust estimate of the velocity signal from location, in this instance employing a real-time computer vision approach rather than traditional techniques based on static filtering models or state observers.

A state observer is a technique that allows us to estimate a variable that can be measured using another system measurement. A high number of state observers assist us in estimating velocity from a robot manipulator's location data. The high gain observers are the most well-known of these strategies. The following is based on the pendulum's mathematical model:

$$\dot{x} = A_0 x + f(x) + g(x)u(t) \tag{2}$$

Where:

$$A_0 = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}$$

$$f(x) = \begin{pmatrix} 0 \\ -\frac{g}{l}\sin(x_1) - \frac{g}{l}(x_2) \end{pmatrix}$$

$$g(x) = \begin{pmatrix} 0 \\ \frac{1}{ml^2} \end{pmatrix}$$

$$C = (1 \quad 0) \tag{3}$$

As a result, based on the work published in (Celikovskyet al 2015), a high gain observer is constructed for the aforementioned system (1):

$$\dot{z} = A_0 z + f(z) + g(z)u(t) + \Psi(r, l_i)Ce$$

$$e = z - x$$

$$\Psi(r, l_i) = (rl_1 \quad r^2 l_2) \tag{4}$$

Where ψ is the high-gain output feedback ratio, e is the estimation error, and:

$$A_0 = \begin{pmatrix} l_1 & 1 \\ l_2 & 0 \end{pmatrix} \tag{5}$$

Where the spatial velocity is based on the signal generated by the machine vision-based position sensor, and the angular velocity estimate z2 is based on the signal emitted by the machine vision-based position sensor. The gains are the high gain matrix, and the gains 1 and 2 are the gains that make matrix A of (5) stable. Equation (4) shows a high gain observer which is used later.

The fundamental drawback of this sort of method is its sensitivity to noise in the measured output signal. Because of the influence of the high gain on the highest instantaneous noise level, it is known that location signals based on non-invasive methods such as computer vision might produce singularity difficulties. The static low-pass filter, on the other hand, is a sort of open-loop feedback that does not need the calculation of the error signal or the numerical model to be the following first-order system:

$$x_1 = f(t)$$

$$\frac{d\tilde{f}}{dt} = -a\tilde{f} + bf(t) \tag{6}$$

Where f(t) is the signal to be filtered and subsequently derived using Euler's technique with gains a=b, because it is well known that it is required to remove and smooth signals with noise in order to estimate derivatives in real time afterwards, otherwise discontinuities may arise. Static filters are not particularly robust due to their lack of online correction, and they are extremely vulnerable to the type of signal to derive; for example, if the signal to derive contains white noise, this sort of static filter will not function well.

In this case, robust algorithms might be sliding mode approaches, which have exhibited a high level of resilience to sudden shocks and noise in analog and digital signals. The "super twisting" algorithm, also known as Super Twisting, is a fantastic approach. In the presence of disturbances, this approach allows us to estimate continuously differentiable functions of a signal. The super twisting controller or any other sort of single degree control system with a single output signal is employed for systems with a unit relative degree (as illustrated in the system described in (1)). (Labbadi et al 2020). To stabilize the system with those of a relative degree larger than 1, however, a controller must forcibly regulate all of the system's states. To estimate using real measurements, a differentiator or observer is necessary. Popular high-gain linear observers are incapable of limited time-in-time stabilization because they only provide asymptotic stability in an equilibrium state (Perez-Ventura et al 2019). In the presence of noise, the sliding-mode differentiator enables finite-time estimate (Shtessel et al, 2014). As a result, the following distinguishing factor is proposed:

$$\dot{z}_1 = \lambda_1 |z_0 + f(t)|^{0.5} sign(Ce) + z_2$$

$$z_2 = -\lambda_0 sign(Ce)$$

$$e = z - x$$

$$C = (1 \quad 0) \tag{7}$$

Where z2 is the robust velocity estimation that is utilized directly with the computer vision location signal, 1 and 0 are the two gains of this sort of estimator or observer, and the sign function is the representation of the sign function of the error variable e. Finally, computer vision is a strong tool that allows us to apply matrix techniques to measure the position of an object or device. When compared to traditional optical sensors, it offers the benefit of being non-invasive. As a result of the need to automate systems based on fourth-generation technologies, it is necessary to consider the need to use this type of algorithm as a source of measurement. As a result, we plan to use it as a means of angular estimation to estimate the angular velocity in real time with the three previous algorithms in this work.

3. MATERIALS, METHODS, AND EQUIPMENT

The NVIDIA Jetson Nano, according to (NVIDIA, 2021), is a compact computer that can perform various artificial intelligence algorithms, including neural networks, for applications such as image classification, object recognition, segmentation, and so on. All of this is done on a 5-volt platform. In this situation, two algorithms are used, one for tilt detection and the other for artificial intelligence tilt detection. In this study, a device of this sort is employed, with artificial vision algorithms written in Python and based on the Open-Source Computer Vision Library (Bradski, et al. 2005), an open-source library with a large number of artificial vision algorithms.

3.1 Algorithms for computer vision

The usage of Open-Source Computer Vision Library (OpenCV) routines-based algorithms is offered as the algorithm. The paper proposes a new form of optical instrument made up of NVIDIA Jetson Nano, digital cameras, and a visual set point to assess the angular location of the robotic device using computer vision technology. Displacement measurements were carried out using the OpenCV routines findChessboardCorners and cornerSubPix. On the platform, five optical settlement instruments were placed for field testing. For long-term settlement monitoring, the optical instrument is generally more cost-effective than the IOT-based equipment. This artificial vision algorithm operates at 9 ms ± 1 ms.

3.2 Hardware

A 6-volt motor with a nominal angular speed of 320 RPM, a metallic gear system, and a torque of 2kgf/cm was employed to create the manipulator structure. Its measurements are 35.5 x 12 x 10 mm, and it weighs 9 grams.

The camera sensor is a Sony IMX219, 8 Megapixel, 3280 x 2646 pixel capture resolution and 160° viewing angle and 9 ms ± 1 ms of sampling time. It takes a dark-colored backdrop of the manipulator for the vision system, and the mass of the pendulum has a pattern that the vision system detects, recalling that the angular position can be approximated using this pattern.

A NVIDIA Jetson Nano is used for processing, it has a 1.43 GHz Quad-core ARM processor, with 4 GB of RAM, 64-bit, LPDDR4 25.6 GB/s memory, NVIDIA L4T operating system with Linux Kernel.

Figure 2 shows the connection diagram of the equipment used for the tests performed on this system. NVIDIA Jetson Nano is connected to Arduino UNO, and this is linked to MATLAB. In the other part of the diagram is the motor coupled to inverted pendulum, controlled by another Arduino UNO.

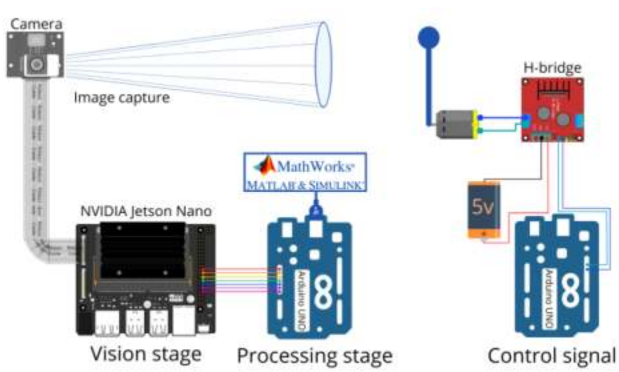

Figure 2. Visual diagram of the hardware and software used in this project.

4. RESULTS IN REAL TIME

The following are the findings of a real-time experiment in which the vision algorithms, observers, and state estimations were programmed in 200 seconds. The technique and hardware used in the preceding part were used to carry out the task online. The gains are the same for all three methods, and they will be compared using the two indices mentioned above. Figure 3 depicts the voltage signal necessary to create the desired oscillatory behavior. Figures 4 and 5 illustrate the location and velocity estimate signals, respectively. The state estimate based on the mathematical model of the basic robotic device described in equation in (1) is proposed in MATLAB Simulink 2018 b language. Where a1 = 98.1, a2 = 0.6, and b1 = 4000 are the parameters of the functions f(x) and g(x). It is suggested to employ a Dorman-Price algorithm of order 45 in a period of 12 seconds. To make it more realistic, white noise with a frequency of 0.1 is suggested. We suggest using an observer in the system in (4) with a projected high gain of r = 10, l1= -10, and l2 = -5, and an output signal y = x1. It is suggested that a gain of 1 = 800 and a gain of 0 = 800 be used in the case of the sliding mode differentiator presented in (7). A = b = 1 is proposed for the situation of the static differentiator in (6).

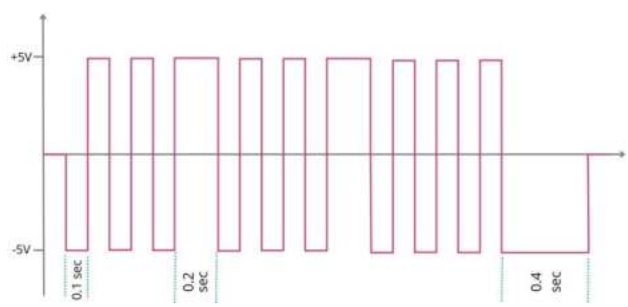

Figure 3. Voltage signal sent to the motor to produce the torque used in the experiment.

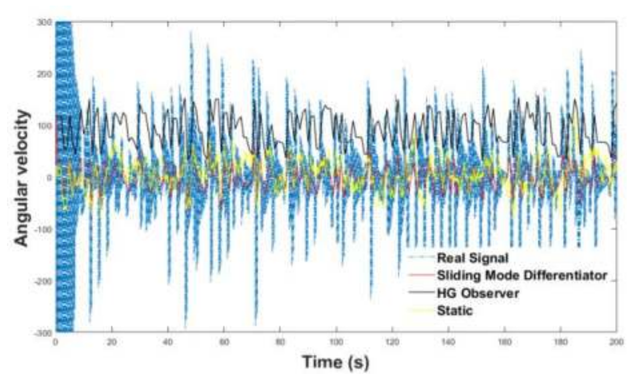

Figure 4. velocity signal using the 3 estimators. Observer (4), static filter (6) and differentiator (7).

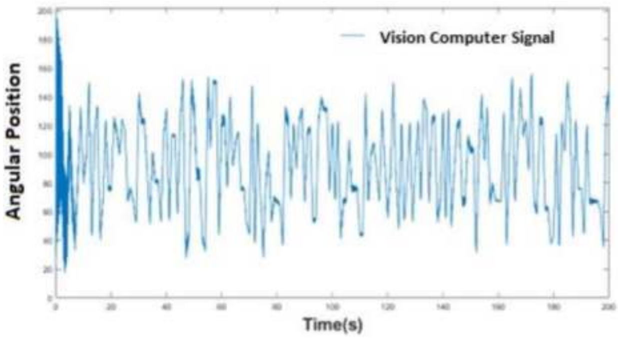

Figure 5. Position signal obtained by computer vision algorithms using the NVIDIA Jetson Nano platform.

In order to compare the different performances, it is proposed to use the Integral of the absolute value of the error (IAE) and Temporal Integral of the absolute value of the error (ITAE) as performance indices to diagnose the best performance in this simulation stage (Marzaki et. al 2015).

$$ITAE = \int t|e|\, dt$$

$$IAE \ = \int |e|\, dt \qquad (8)$$

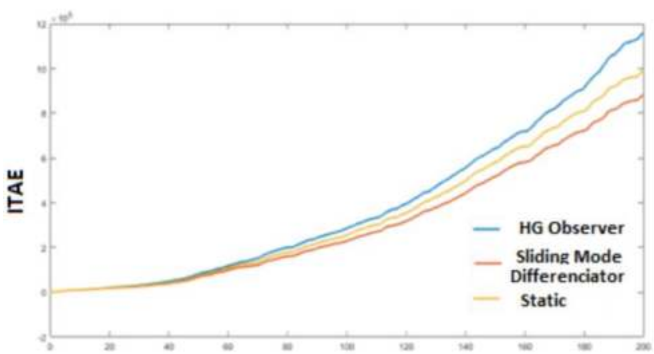

Figure 6. Calculation of the ITAE error rate signal by 10^5 of the real-time experiment.

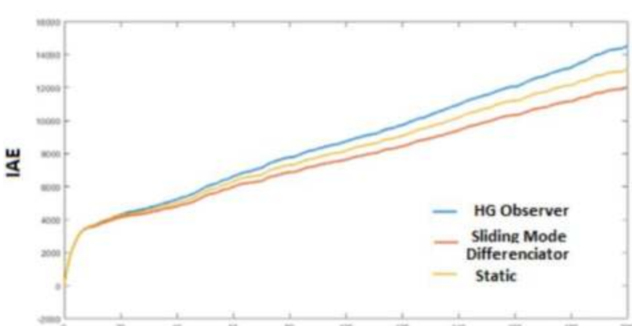

Figure 7. Calculation of the IAE error rate signal of the real-time experiment.

It can be seen in Figures 6 and 7 the two indexes are shown for the evaluations of the error rate ITAE and IAE it is easy to see that the one differentiated by sliding modes is superior to the other two differentiators. This is due to the noise signals present in the real position signal.

5. CONCLUSIONS

This paper presented a novel application and combination of automatic control algorithms and artificial intelligence for angular velocity estimation of a first order manipulator device using computer vision and three state estimation algorithms: sliding mode differentiator, high gain observer, and static filter on an NVIDIA Jetson Nano platform as a position estimation platform. The results of numerical simulations as well as real- time findings were given. The sliding mode differentiator is considerably superior in angular velocity estimation for position signals using artificial intelligence sensors, as demonstrated by the ITAE and IAE indices. This study shows that combining artificial vision with automated control approaches to estimate the angular velocity of high-speed signals, such as those described in this study, yields outstanding results. High gain observers, which are often superior to the Kalman filter and also to a high gain observer, were proven to be superior to sliding mode approaches. This research may be used to calculate the velocity of high-speed moving pictures, such as determining the ratio of autos, people, and objects in general.

REFERENCES

Bradski, G., Kaehler, A., & Pisarevsky, V. (2005). Learning-based computer vision with intel's open-source computer vision library. Intel technology journal, 9(2).

Celikovsky, S., Torres-Munoz, J., Rodriguez-Mata, A., & Dominguez-Bocanegra, A. R. (2015, October). An adaptive extension to high gain observer with application to wastewater monitoring. In 2015 12th international conference on electrical engineering, computing science and automatic control (cce) (pp. 1-6). IEEE.

Cosenza, M. (2015). Mecánica Clásica. Universidad de los Andes (ULA). Facultad de Ciencias. Departamento de Física. Mérida-Venezuela (Publicación Electrónica), 133-141.

Fernández Llorca, D., Hernández Martínez, A., & García Daza, I. (2021). Vision-based vehicle speed estimation: A survey. IET Intelligent Transport Systems, 15(8), 987-1005.

Khalil, H. K. (2002). Nonlinear systems third edition. Patience Hall, 115.

Kouro, S., & Musalem, R. (2002). Control mediante lógica difusa. Técnicas Modernas en Automática, 1, 1-7.

Labbadi, M., Boukal, Y., & Cherkaoui, M. (2020). Path following control of quadrotor UAV with continuous fractional-order super twisting sliding mode. Journal of Intelligent & Robotic Systems, 100(3), 1429-1451.

Marzaki, M. H., Tajjudin, M., Rahiman, M. H. F., & Adnan, R. (2015, May). Performance of FOPI with error filter based on controllers performance criterion (ISE, IAE and ITAE). In 2015 10th Asian Control Conference (ASCC) (pp. 1-6). IEEE.

Messner, B., Tilbury, D., Hill, R., & Taylor, J. D. (2017). Control Tutorials for Matlab and SIMULINK–Inverted Pendulum: System Modeling. Univ. of Michigan, Carnegie Mellon Univ., Univ. of Detroit Mercy.

Nasir, A. N. K., Ismail, R. M. T. R., & Ahmad, M. A. (2010). Performance comparison between sliding mode control (SMC) and PD-PID controllers for a nonlinear inverted pendulum system. World Academy of Science, Engineering and Technology, 71, 400-405.

Ooi, R. C. (2003). Balancing a two-wheeled autonomous robot. University of Western Australia, 3.

Pérez-Ventura, U., & Fridman, L. (2019). Design of super-twisting control gains: A describing function-based methodology. Automatica, 99, 175-180.

Rodríguez-Rangel, H., Morales-Rosales, L. A., Imperial-Rojo, R., Roman-Garay, M. A., Peralta-Peñuñuri, G. E., & Lobato- Báez, M. (2022). Analysis of Statistical and Artificial Intelligence Algorithms for Real-Time Speed Estimation Based on Vehicle Detection with YOLO. Applied Sciences, 12(6), 2907.

Shtessel, Y., Edwards, C., Fridman, L., & Levant, A. (2014). Sliding mode control and observation (Vol. 10). New York: Springer New York.

Vidyasagar, M. (1994). Nonlinear Systems Analysis.