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RESEARCH ARTICLE

Optimal Signal Processing for Steady Control of a Robotic Arm Suppressing Hand Tremors for EOD Applications

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ABSTRACT Teleoperated robotics in recent years has proven to be valuable support in EOD tasks; a remarkable improvement in the systems that control these robots has been the Natural User Interfaces (NUI); however, the research that implements this type of system does not focus on the stability of the robotic arm movements, necessary for this type of applications due to the danger of working with explosives. In this paper, we propose the implementation of an Optimal Signal Processing for a NUI interface based on the Leap Motion (LM) controller. The main objective of this research is to correctly identify the intentional movements of the operator, achieve high stability of the robotic gripper and suppress the physiological tremors from the hand of the operator, considering not to increase the mental workload and not decrease the usability of the system. The signal processing proposed in this paper is composed of three filtering algorithms: Kalman, FIR, and moving average with a threshold. In addition, the obtained results are compared with the most representative processing of recent research using LM for robotic arm control. To evaluate and validate the proposed signal processing, a target path tracking test, a stability analysis of the robotic gripper, and a performance analysis in the execution of Pick and Place tasks, NASA-TLX and SUS questionnaires are developed. Finally, the proposed Optimal Signal processing is implemented in the DOBOT-MAGICIAN and tested by police officers of the EOD Unit-Arequipa (UDEX-AQP); the results indicate a reduction of the average Vibration of 31.61% and the Target Path Tracking error of 67.57%.

INDEX TERMS EOD robot, hand tremors, signal processing, teleoperation, NUI interface, leap motion.

I. INTRODUCTION

The development of robotics and telecommunication technologies has increased in recent years; this has led to an increase in teleoperation research that allows humans the ability to remotely control an external system, e.g., a robot, in the manner of an avatar to complete various tasks [1]. On the other hand, Explosive Ordnance Disposal (EOD) tasks have benefited from the intervention of robots capable of providing support and, in some cases, relegating a human agent in the direct intervention of these tasks. Several analyses have been carried out in different research centers [2], [3], [4], [5], [6], [7], [8]. At a local level, studies conducted on UDEX-AQP interventions from 2013 to 2020 show that an EOD robot would have efficiently participated in 91% of cases in explosives disposal [7], [8].

In this context, EOD robots have been the focus of several types of research for their performance improvement; one of the most promising aspects to be developed is the human-robot interface (HRI) [9], [10], [11], [12] that connects the intentions of operator and knowledge with the capabilities of robot. Considering the complexity involved in classical EOD robot controls that are composed of a case equipped with button panels. In response to these types of

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problems, recent research in robotic interfaces focuses on Natural User Interfaces (NUI) since these interfaces are based on the own gestures of human to communicate with the robot and give it interpretable instructions [14]. In this context, in [15] is pointed out that a good gesture design should possess several important characteristics, such as that gestures should be natural, consistent, and easy to express. Under this premise, multiple sensors and systems capable of recognizing and interpreting human gestures have been developed to perform determined actions in virtual, teleoperated, surgical environments, etc. [16], [17], [18], [19].

One of the interfaces that have demonstrated versatility to control multiple systems is the Leap Motion (LM) sensor [20], [21], [22], [23], [24], [25], [26]. This is a motion sensor that allows us to acquire and interpret gestures that we make with our hands in the workspace captured by the device. This sensor is capable of capturing gestures at a rate of 10 to 290 frames per second in a field of view of 150 degrees [27], [28]. However, directly using the LM to control an EOD robotic arm without any signal processing results in unstable and vibrational or oscillating movements of the robot gripper, which do not correctly represent the intentional movements of operator and compromise the electromechanical systems of the EOD robot; these problems can trigger catastrophic incidents due to the dangerousness of EOD tasks when dealing with highly unstable explosives. These problems are caused by different noises that affect the operation of the robotic system, such as physiological tremors, involuntary movements of the operator, and noises inherent to the operation of the LM, which takes indirect measurements of the hand of operator using infrared cameras.

Different solutions to these problems have been presented in other research studies, in [29] an Average filtering algorithm with treshold is used to determine the control signal, in [30] a speed-based lowpass filter is used, which changes the cutoff frequency of the lowpass filter according to the speed of the palm of the hand, in [31] a Delta Robot is presented that uses its own frame structure so that the noises do not have a considerable impact on the robot movements, in [19] a mean filter is used, in this work there are also specific hand gestures that are recognized, to differentiate even better these gestures a treshold is used to manage the sensitivity of the system, in [32] a filtering of the signal is performed using an Improved Kalman Filter and an Interval Kalman Filter, however the resulting signals still have a slight noise (about 1mm) that are interpreted in the control signal, in [33] a cost function is introduced to the signal conditioning to achieve a smooth movement, although, the resulting signal is reduced in accuracy, in [16] a Kalman filter is used for the control of a surgical robot and in [17] a similar system is proposed for the in-depth study of the hand tremors of operator and their impact on surgical operations. These solutions propose different Leap Motion signal conditioning methods; however, these proposed methods do not focus on suppressing the physiological tremors of the hand of the operator that could cause vibratory movements in the robotic gripper during EOD tasks, where a high stability of the robotic arm, a correct identification of the operator's intentional movements must be prioritized, and the usability of the system and mental workload must also be taken into consideration.

In this paper, we present an optimal signal processing of the LM sensor to be used in EOD tasks, correctly identifying the intentional movements of the operator, achieving an optimal stability of the robotic gripper suppressing the physiological tremors of the hand of operador and the LM noises, considering the mental workload of operator, the usability achieved and improving the performance in the execution of EOD tasks, this signal processing is implemented through a combination of the following filters: Kalman, FIR, and Average moving filter with a threshold in that order.

The main contributions of this paper are listed below:

- An optimal signal processing is proposed for the suppression of LM sensor noise as well as the physiological hand tremors of operator. The optimal signal processing is composed of a cascaded configuration by Kalman filter, FIR, and moving averaging with threshold.
- A comparative analysis with recent research focused on LM for robotic arm control is performed to validate the optimal processing proposed in this paper.
- A suitable setup is implemented to validate the performance of all types of signal processing adapted to a robotic arm for the evaluations of target path tracking, vibration, performance, mental workload, and usability.

This paper is organized as follows: In the second section, we give an exhaustive review of the research on the use of LM with different robotic arms. In the third section, is presented our approach to the work and the objectives to be achieved, as well as a description of the systems to be evaluated in this research. In the fourth section, is presented the hypotheses for the correct development of the methodology and a subsequent evaluation and discussion. In the fifth section, we review the physiological and system signals to contextualize the algorithms used in Optimal Signal Processing. In the sixth section, the methodology is presented in detail, implementing the filtering algorithms. In the seventh section, we detail the evaluations and tasks that were performed on the participants, detailing the considerations that were taken into account during the evaluations. In the eighth section, we discuss the results obtained through statistical and qualitative tests. In the ninth section we discuss the analysis made in the eighth section. In the tenth section, we discuss the limitations and the future work for this research. In the eleventh section we discuss the design and research implication obtained from this research. Finally, in the twelfth section, we mention the final conclusions reached with the development of this research.

II. RELATED WORK

In the teleoperated robotics area, the NUI interfaces propose to improve the HRI to make the control of teleoperated robots an intuitive task; for this, it is necessary to achieve

TABLE 1. State of Art Research on Robotic Systems controlled by LM sensor.

Lit	Robotic System	Signal Processing	Stability	Precision	Target Path Tracking Evaluated	Hand Tremors
[26]	Surgical Robot	Kalman filter	Medium	High	Yes	Yes
[2]	Dobot Magician	Kalman Filter	Low	Medium	No	No
[20]	Surgical Robot	Kalman Filter	Low	High	Yes	No
[16]	GOOGOL GRB3016	Interval Kalman Filter, Improved Particle Filter	Medium	High	No	No
[22]	GOOGOL GRB3016	Particle Filter, Kalman Filter	Medium	High	No	No
[15]	UR-5 Robot	Mean Filter, thresholds for gestures detection	Low	Low	No	No
[5]	Robot SCARA	Average filtering Algorithm with treshold	Not mentioned	Not mentioned	No	No
[13]	UR-10 Robot	Speed-based low-pass filter	Low	High	No	No
[17]	UR-5 Robot	Cost Function for smooth movement	Medium	Medium	No	No
[18]	COCOHRIP Collaborative Robot	Not mentioned	Not mentioned	Not mentioned	No	No
[14]	Delta Robot	Not mentioned	Not mentioned	Not mentioned	No	No

appropriate processing of the signal obtained from the NUI interface. In [29] is used a SCARA robotic system using the LM sensor as controller, to eliminate noise is proposed an Average filtering with threshold, this algorithm calculates an average of the positions obtained in the frames captured by the LM and applies a threshold to filter the control signal, Chen and Ma in [30] use a Noise Suppression with a Speed-based low-pass filter, which changes the cutoff frequency of the low-pass filter depending on the velocity obtained from the palm of the hand, in [31] a robot in Delta configuration is implemented using a Leap Motion sensor for its direct control, in other research works such as [32] and [35] much more complex algorithms are used to eliminate noise from the LM signal, such as the Interval Kalman Filter and an Improved Particle Filter, these filters significantly improve the accuracy obtained by the sensor, in [34] a collaborative human robot system is used to determine human hand gestures using Leap Motion, this system does not need a prior processing of the signal because the objective of this research is the detection of gestures pointing to a specific dot in a 2D plane. In [32] and [35], it is proposed to evaluate the Target Path Tracking, which is implemented in the gripper of the robotic arm GOOGOL GRB3016; this analysis shows graphically how the robotic gripper copy the movements made by the operator. However, vibrations are still present due to the physiology of the human hand and the noises of the LM. In [5] and [32], advanced algorithms of the Particle Kalman Filter and Interval Kalman Filter are presented, which achieve high precision and estimation of the LM signal at the cost of a high computational load. In the research [16], a Kalman filter controls a surgical robot. In [17], a similar system is proposed for the in-depth study of the hand tremors of operator and their impact on surgical operations.

In Table 1, is presented a comparison between different research focused on HIR using LM-based NUI; these papers are directly related to the objectives and methods proposed in this research; stability, accuracy, identification of the intentional movements of the operator, consideration of hand tremors and performance achieved in determined tasks, this information is collected regarding to the graphs and results of each research work and is summarized in four categories as follows:

- Not mentioned: If the work does not require a particular signal processing characteristic.
- Low: A relatively low value of the characteristic.
- Medium: A value that does not consider the feature as optimal but shows some level of performance.
- High: The characteristic achieves an optimal level of performance.

In Table 1 is summarized the signal processing used in the most representative research that uses the LM sensor to control robotic arms, detailing the sensor and the robotic system used, the stability and accuracy achieved with each system are summarized by regarding their graphs and data in a referential mode. It is also considered if these works perform a target path tracking analysis to study the identification of the intentional movements of the operator. Finally, information is collected from the works that focus on physiological hand tremors. The following information was found:

- The vast majority of research prioritizes system accuracy and sensitivity over stability.
- Multiple papers take Target path tracking to evaluate the intentional movements of the operator.
- Only one paper considers hand tremors when controlling a robotic system with the LM.
- Kalman filter algorithm is one of the most used for signal processing, mentioning its value to estimate the hand position of the operator correctly.
- Only one of the papers focused on EOD studies the usability and mental workload of the system using questionnaires such as NASA Task Load Index (NASA-TLX) and System Usability Scale (SUS).

III. OUR APPROACH

The signal processing proposed in this paper aims to adapt the signal from the LM sensor for EOD tasks. The requirements for this type of application, due to the volatile characteristics of explosives and the complexity of operating a remote robot, are detailed below:

- The robotic gripper must perform non-vibratory movements when held in a fixed position.
- The system should reproduce the intentional movements of the operator on the robotic gripper.
- The performance achieved by the operators performing Pick and Place tasks must be considered.
- The mental workload and the usability of the proposed system should also be taken into consideration.

Goyzueta in [2] has oriented the use of a Kalman Filter based processing to have an optimal estimation of the hand position of the operator to control the robotic arm by LM due to the characteristics of the LM sensor and the noises it has, the Kalman filter is optimal to obtain more accurate information of the hand position. However, although a correct hand estimation is obtained, physiological tremors caused by the musculoskeletal composition of the operator are still present. In [16], [17], a Kalman filter is also used for the control of a surgical robot and to study exhaustively tremors of the user hand concluding the significant incidence of these tremors on the movements of the robotic gripper. In [36], [37], [38], these tremors are detailed and classified into action and rest tremors. The action tremors, in turn, are divided into intentional and postural tremors, each one with a different frequency range.

Considering these research works on robotic arms controlled by a contactless sensor such as the LM, as can be seen in Table 1, it is the Kalman filter-based processing that is the most commonly used due to its optimal observer characteristics. However, as also seen in [16], physiological tremors must be considered in the control of the robotic arm. Because these tremors have specific frequency ranges, in this research, we propose a signal processing composed for a FIR filter to remove intentional tremors, a moving averaging filter to remove postural tremors and a Kalman filter that estimates the real position of the hand of the operator.

To evaluate the performance of this new signal processing on the requirements mentioned for EOD applications, we made a comparison of the systems:

- System 1: Composed of a Kalman Filter.
- System 2: Composed of a Kalman filter, an FIR filter, and an average moving filter.

System 1 is composed of a Kalman Filter. In [2] is used this filter to control a robotic arm using leap motion oriented to EOD applications, performing an in-depth analysis of the performance of this interface compared to traditional controls such as keyboards or keypads. Korayem in [16] uses the Kalman filter to eliminate noise in the input of his system for a surgical application, and in [17] it studies in depth the physiological tremors of the operators using the LM sensor to measure them and the fast Fourier transform to determine their spectral range, concluding that physiological tremors constitute a significant contributor to end-effector vibrational motions, while Kalman filter extensions are used to minimize overall system noise. Being the Kalman filter is one of the most commonly used processing in the area of robotic arm control with contactless systems, we use this processing as a comparison for our proposed system, as well; this comparison will allow us to know the effect of selectively suppressing physiological tremors on the performance of the proposed system.

System 2 is the Optimal Signal Processing proposed in this research. The noises that enter the signal processing come from two sources: the physiological hand tremors and the Gaussian behavior noises of the LM sensor as can be seen in Figure 1; in order to treat these two noises appropriately is proposed in System 2 a combination of three filters that are implemented in stages, starting with the Kalman filter that eliminates high-frequency noises that have Gaussian behavior, and estimates in an optimal way the position of the hand, including the tremors that the operator may have in his upper limb. A FIR filter is implemented to eliminate these low-frequency vibrations during intentional movements made by the operator. Finally, to eliminate postural tremors, a Moving Average filter with a threshold is implemented, which also eliminates unintentional movements of the operator due to fatigue or loss of the LM sensor's working space. These physiological tremors and system noises are detailed in the fourth section. Figure 2 illustrates the schematic diagram of the two systems mentioned above.

IV. HYPOTHESES

The aim is to evaluate the performance of System 2 compared to System 1 based on the four hypotheses described below, which will be evaluated in Section VI.

Hypothesis 1: Lower perceived mental workload and higher usability will be perceived in System 2 compared to System 1.

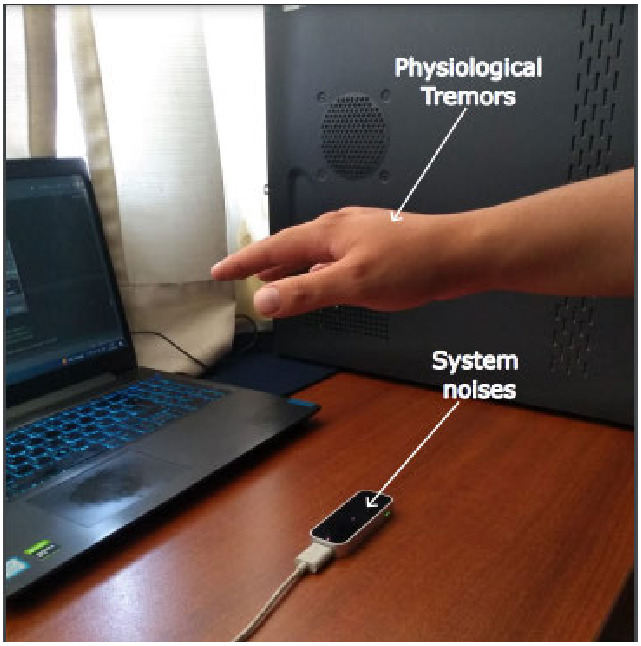

FIGURE 1. Physiological and Gaussian noise sources considered for this research.

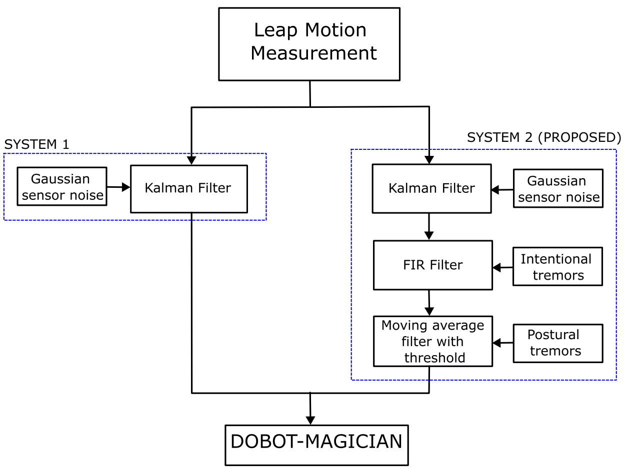

FIGURE 2. Schematic diagram of the two systems proposed in our approach.

Hypothesis 2: The task completion time will decrease in System 2 compared to completion time measured with System 1.

Hypothesis 3: The average vibration registered on the robotic gripper will be drastically reduced in System 2 compared to System 1.

Hypothesis 4: The target path tracking will improve in System 2 compared to System 1.

The characteristics proposed to be compared and analyzed in this research are divided into two types based on their metrics: objective and subjective, as detailed in Table 2.

With these hypotheses, we aim to test a better performance in System 2 compared to System 1 in an EOD applications approach by focusing on the suppression of physiological tremors.

TABLE 2. Summary of Objectives and Subjectives measurements.

Measurement	Type	Metrics
System Usability	Subjective	Questionnaire [*Likert Scale*]
Cognitive Workload	Subjective	Questionnaire [*Likert Scale*]
Completion Time	Objective	Seconds [*s*]
Target Path Tracking	Objective	Milimeters [*mm*]
Average Vibration	Objective	Acceleration [*m/s*]

V. SYSTEM AND PHYSIOLOGICAL SIGNALS

In this section, we describe the signals and noises that affect the final operation of the robotic arm; multiple studies have been performed regarding these noises, and for this paper, is considered as the priority ones the physiological hand tremors and the estimation of the hand position of the operator detected by the LM sensor. In [17] and [37], it is mentioned that physiological tremors are divided into rest and action tremors. In turn, action tremors can be divided into kinetic, intention, and postural tremors [17]. Kinetic tremors are of very low amplitude, so they are not considered for our approach. During an operation with the LM sensor, intention tremors occur when a limb is moved toward a target position, and postural tremors occur when a limb is placed in a fixed position for a while. Furthermore, it must be considered that the LM sensor takes indirect and noisy measurements due to its operating principle based on image processing [16], [32], [35].

A. INTENTIONAL TREMORS

These tremors appear when intentional movements occur; they are characterized for having high amplitude and low frequency throughout the extent of the movement, their frequency is variable in each case, but they are considered to occur generally from 3 to 10 Hz [16], [17], [38]. During a regular operation with the LM sensor, the operator must perform multiple intentional movements to control the robotic gripper and bring it to a target position, so intention tremor is present in most of the operations with the LM sensor.

B. POSTURAL TREMORS

These tremors are present when a limb is held in a fixed position against gravity. They may be altered by specific positions or tasks and may also be associated with dystonia, a disorder in which involuntary contractions of increased amplitude occur during sustained limb positions [16], [17], [38]. This type of tremor usually has a frequency of 5 to 8 Hz. Due to the characteristics of the robotic arm and its placement time in a new setpoint, the operator must maintain during the whole control process different fixed positions, waiting for the robot to reach the instruction received by the LM and the hand position it captures, this is the reason that postural tremors are also considered within a operation with the LM sensor.

C. HAND POSITION ESTIMATION

The LM sensor captures information from the hand through image processing; because the sensor is not directly coupled to the hand of the operator, this position measurement is considered indirect; added to this, the noisy signals typical of this type of sensor and electrical signals [29], [30], [31], [32]. This noise can be considered Gaussian, and due to the lack of a direct measurement of the hand position, a Kalman filter is commonly used for an adequate estimation [16], [32].

VI. METHODOLOGY

A. EQUIPMENT AND SETUP

The robotic arm used for the testing of the systems is the DOBOT Magician with 5 degrees of freedom, a maximum reach of 320 mm, repeatability of 0.2 mm, with a payload of 0. 5 kg, connected to a Lenovo laptop with 8 Gb of RAM memory, Intel Core i5 9th generation processor in charge of receiving the data obtained by the LM sensor and processing the data with the two proposed systems, this sensor has two IR cameras of 640 × 240 pixels and 3 IR LEDs, with a working area of 60 cm maximum height and a typical field of view of 140 × 120°. A second 15.6-inch 16:9, 1920 × 1080 pixel laptop is used to provide visual support to the test participants and to record the target path. For this purpose, the laptop is connected to a webcam that focuses a visual marker on the robotic arm. The LM sensor is placed in front of the laptop computer in charge of the visual support; these two elements make up the control station, where each participant will be positioned to perform the tasks. For the vibration evaluations, an MPU 6050 accelerometer is used to detect the changes in the acceleration of the robotic gripper; this sensor sends the data to an Arduino UNO to record them. For the pick and place and consecutive pick and place tasks, we use three objects that simulate suspicious packages with the characteristics mentioned in [7], as can be seen in Figure 3. The complete setup can be seen in Figure 4.

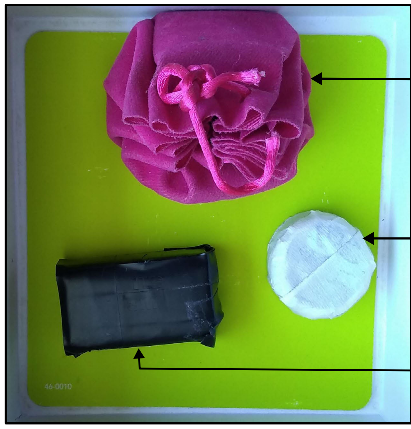

FIGURE 3. Objects which simulate suspicious packages used for Task 1 and Task 2.

B. SIGNAL PROCESSING

The proposed optimal processing is composed of the cascaded combination of 3 filters: Kalman filter, FIR, and moving average with a threshold. The algorithm and programming were developed in Python programming language. Figure 5 shows a flow diagram representation of the proposed system, starting with data acquisition from the Leap Motion sensor. The Kalman filter is responsible for removing the high frequency Gaussian noise from the sensor and starts by using previous data, such as the LM sensor signal. In the second stage, a FIR filter with 8 Hz cutoff frequency is responsible for removing intentional tremors from the operator, and finally, in the third stage, a moving average filter with a threshold is implemented to remove postural tremors. These frequential characteristics of the Gaussian noise from the LM sensor and the physiological tremors of the hand of the operator are described in Section V.

For the processing of the leap motion signal, it is necessary to obtain the dynamics of the human hand, which is presented below in the discrete domain time state space model [32], [35]:

$$\begin{cases} x_k = F_k.x_{k-1} + G_k.u_{k-1} + w_{k-1} \\ z_k = H_k.x_k + v_k \end{cases} \tag{1}$$

With:

$$\begin{aligned} x_k &= [p_x, v_x, a_x, p_y, v_y, a_y, p_z, v_z, a_z] \\ G_k &= [0, 0, 0, 0, 0, 0, -g.\frac{t^2}{2}, -g.t, 0] \end{aligned} \tag{2}$$

where x_k and G_k represent the vector of states and the control matrix, respectively, the vector of state measurements is represented by z_k, where H_k is the observation matrix. The noises w_k and v_k represent the process noise and measurement noise, respectively. Finally, the state transition matrix F_k can be given as:

$$F_k = \begin{bmatrix} 1 & t & \frac{m_{X_x}t^2}{2} & 0 & 0 & \frac{m_{Y_x}t^2}{2} & 0 & 0 & \frac{m_{Z_x}t^2}{2} \\ 0 & 1 & m_{X_x}t & 0 & 0 & m_{Y_x}t & 0 & 0 & m_{Z_x}t \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{m_{X_y}t^2}{2} & 1 & t & \frac{m_{Y_y}t^2}{2} & 0 & 0 & \frac{m_{Z_y}t^2}{2} \\ 0 & 0 & m_{X_y}t & 0 & 1 & m_{Y_y}t & 0 & 0 & m_{Z_y}t \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & \frac{m_{X_z}t^2}{2} & 0 & t & \frac{m_{Y_z}t^2}{2} & 1 & t & \frac{m_{Z_z}t^2}{2} \\ 0 & 0 & m_{X_z}t & 0 & 0 & m_{Y_z}t & 0 & 1 & m_{Z_z}t \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

The algorithms of each filtering stage and their characteristics are detailed below:

Kalman Filter: The Kalman algorithm is presented in the algorithm 1, where the initial state estimate x_0 and the covariances P_0 R, Q and L are the inputs to the algorithm.

FIR Filter: The FIR algorithm is presented in the algorithm 2. In this paper, we use the Kaiser window for the filter design, which has as input parameters: z_k, which is the output of the Kalman filter, $\Gamma = 60\ dB$ is the upper limit of the deviation of the magnitude of the filter frequency response, $\Delta = 0.016$. It is the width of the transition region, and finally, considering the frequencies of the intentional tremors of the hand we determine a cutoff frequency of 8 Hz.

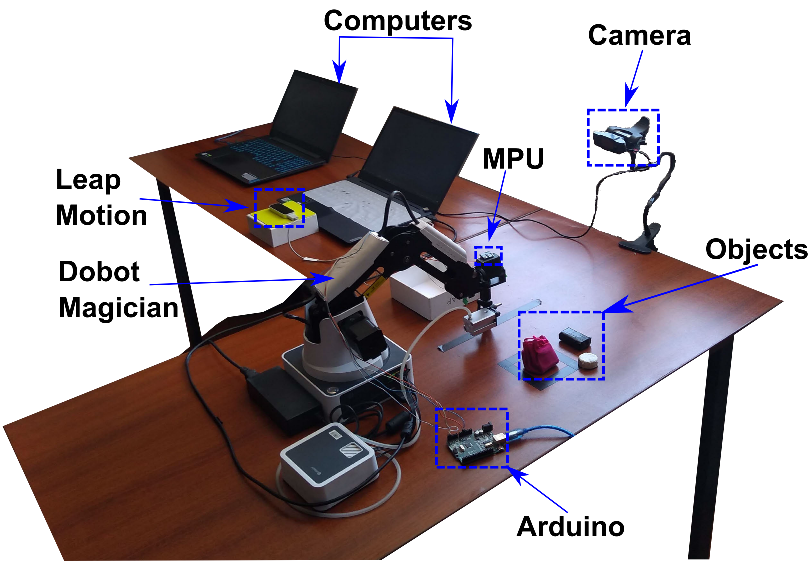

FIGURE 4. **Overview of the implemented test setup for Target Path Tracking, Vibration, Performance, Mental Workload and Usability Evaluations.**

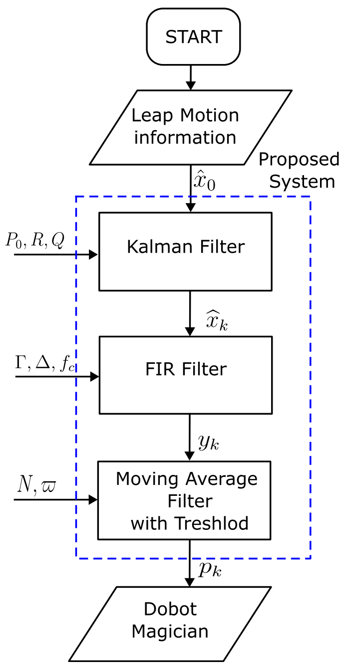

FIGURE 5. **Flow diagram of the proposed Optimal Signal Processing.**

Moving Average Filter with Treshold: The algorithm of the moving average filter with threshold is presented in the algorithm 3; as input parameters, it presents the output y_k and the number of coefficients N of the FIR filter. w is the threshold and is adjusted to eliminate the postural hand tremors of the operator.

C. TASKS

The tasks were carried out with the participation of a group of UDEX-AQP agents in order to validate the proposed optimal signal processing for EOD applications. Five parameters are evaluated: performance, target path tracking, vibration, mental workload, and usability. Implementing three tasks: pick and place, consecutive pick and place, and stability.

Algorithm 1 Kalman Filter

Data: $\hat{x}_0, P_0, R, Q$
Result: $\hat{x}_k$
begin
  for $k = 1 : M$ **do**
    1. a priori covariance estimation:
    $P_k = F_{k-1}P_{k-1}F_{k-1}^T + Q_k$
    2. calculation of Kalman gain:
    $K_k = P_k H_{k-1}^T (H_{k-1}P_k H_{k-1}^T + R_k)^{-1}$
    3. state estimation:
    $\hat{x}_k = F_{k-1}\hat{x}_{k-1} + K_k(z_k - H_k\hat{x}_{k-1})$
    4. a posteriori covariance estimation:
    $\hat{P}_k = (I - K_kH_k)P_{k-1}(I - K_kH_k)^T + K_kR_kK_k^T$
  end for
end

1) TASK 1: PICK AND PLACE

This task consists of lifting an object that simulates a suspicious package and placing it in a desired deposit as shown in the Figure 6, each agent must perform the task three times with different objects and each task increases the complexity in the geometric shape of the object.

2) TASK 2: CONSECUTIVE PICK AND PLACE

This task consists of performing a pick and place task consecutively, two areas are designated where there is a different object in each space. The agent must pick up the first object and place it where the second object is located and vice versa as can be seen in Figure 7.

Algorithm 2 FIR Filter

Data: z_k, Γ, Δ, f_c
Result: y_k
begin
  for $k = 1 : M$ **do**
    1. calculation of Kaiser window parameters:
    $[N, \beta] = kaiserord(\Gamma, \Delta)$
    2. calculation of filter coefficients:
    $[b_k] = firwin(N, f_c, \text{window} = (\text{'kaiser'}, \beta))$
    3. state estimation:
    $y_k = \sum_{i=0}^{N-1} b_k . z(k-i))$
  end for
end

Algorithm 3 Moving Averaging Filter With Threshold

Data: y_k, N, ϖ
Result: p_k

$$\delta_1 = \frac{\sum_1^{\frac{N}{2}} y_k}{\frac{N}{2}}$$

$$\delta_2 = \frac{\sum_{\frac{N}{2}+1}^{N} y_k}{\frac{N}{2}}$$

for $k = 1 : M$ **do**
  if $|\delta_1 - \delta_2| > \varpi_{max}$ **then**
    $p_k = \delta_2$;
  else
    $p_k = \delta_1$;
  end
end for

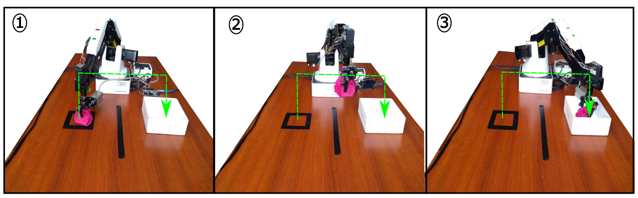

FIGURE 6. Pick and Place task for the first object. (1) Robotic gripper picking up the object. (2) Transferring the object. (3) Placing the object in the deposit target.

3) TASK 3: STABILIZE GRIPPER

In this last task, the stability of the robotic gripper is evaluated, where each agent must perform the following task: raise the gripper at its highest point in the working area of the robotic arm, stabilize it for five seconds, then lower the gripper at its lowest point and stabilize for five seconds in the same area as can be seen in Figure 8.

D. PARTICIPANTS

A total of ($N = 10$) participants were required for this research. These agents have experienced police officers from the UDEX-AQP, nine males and one female.

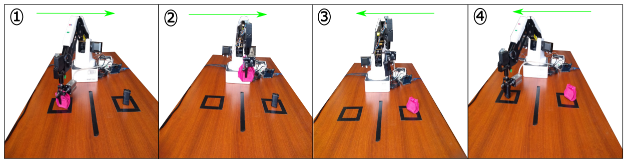

FIGURE 7. Consecutive Pick and Place task. (1) Robotic gripper picking up the first object. (2) Transfer of the first object. (3) Release the first object and pick up the second object. (4) Deposit the second object in the original position of the first object.

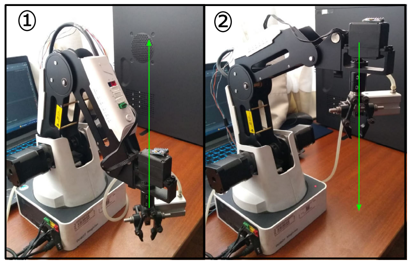

FIGURE 8. Stabilization Task. (1) Robotic Gripper at its lowest point. (2) Robotic Gripper at its highest point.

VII. EVALUATION

To evaluate each system according to the tasks proposed and the hypotheses detailed in section III, Objective and Subjective measurements were differentiated and implemented as detailed below:

A. SUBJECTIVE MEASURES

To evaluate the Cognitive Workload of each system during Tasks 1 and 2, we used the multidimensional assessment tool questionnaire NASA-Task Load Index, known as NASA-TLX, considering six subscales: mental demand, physical demand, performance achieved, effort and frustration. Additionally, to measure the overall usability of each system, we used the System Usability Scale questionnaire, known as SUS, considering a total of ten questions on a five-level Likert scale, ranging from "Strongly Disagree" to "Strongly Agree", evaluating the consistency and complexity of each system. Figures 9 and 10 show the participants (UDEX-AQP agents) being evaluated at the end of the tasks proposed for each system.

B. OBJECTIVE MEASURES

To evaluate the performance achieved by the participants in performing Tasks 1 and 2, the time it took for each participant to perform the tasks was measured. A visual motion capture system using an external webcam was also implemented to track the robotic gripper to the desired trajectory in Task 1, and the root mean square error (RMSE) was measured. Figure 11 shows the participant performing Task 1, and Figure 12 shows a schematic representation of the implemented motion capture system. Finally, in Task 3, we measured the vibration presented by the robotic gripper using the MPU 6050 accelerometer located on the top of the gripper, then, this error was evaluated applying the RMSE.

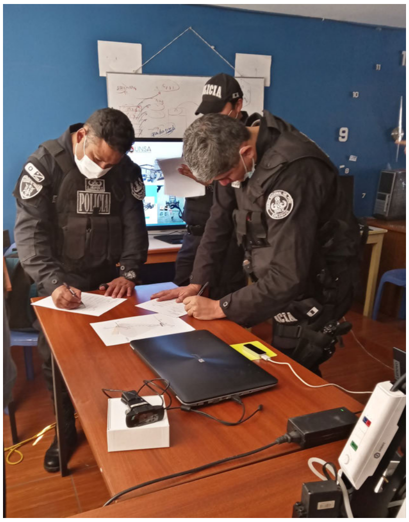

FIGURE 9. UDEX Agents answering the NASA TLX questionnaire after executing the Tasks.

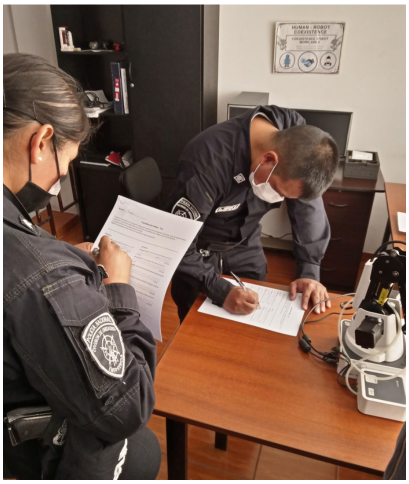

FIGURE 10. UDEX Agents answering the SUS questionnaire after executing the Tasks.

C. PROCEDURE

Before starting the tasks, the participants were informed that two different systems would be evaluated, without indicating which system was the proposed Optimal Signal Processing. Subsequently, each participant was introduced to the operation of the Leap Motion system, as well as the work area and the tasks to be performed. Before each participant formally performed the tasks, they were given a few minutes to familiarize themselves with the interface. Finally, after each task was completed, they were asked to fill out the NASA-TLX and SUS questionnaires after explaining the context of each question in the tests. Simultaneously with the performance tests, target path tracking and vibration tests were performed to ensure that the data obtained in these tasks correspond to typical Pick and Place operations performed by agents experienced with EOD tasks.

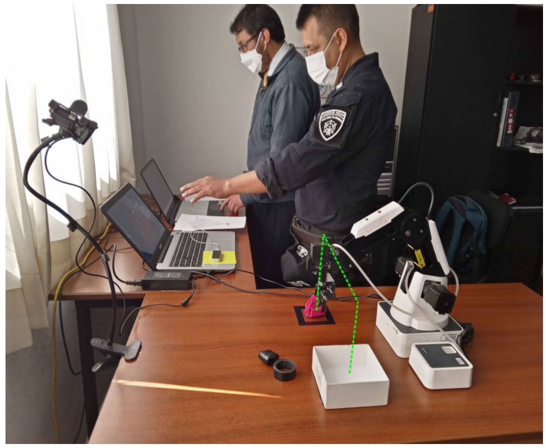

FIGURE 11. UDEX Agent performing Pick and Place Task.

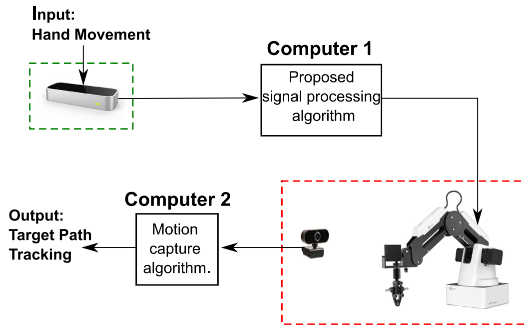

FIGURE 12. Motion capture system used for Target Path Tracking Evaluation.

VIII. RESULTS

The results are divided in analysis techniques and methods, subjective and objective results as follows:

A. ANALYSIS TECHNIQUES AND METHODS

Due to the nature of the evaluation, where we compare two systems measuring parameters in different subjects, an ANOVA analysis for repeated measures (RM-ANOVA) is proposed, this analysis is applied in [1] for evaluate different interfaces; this parametric analysis requires that data obtained to be normal, so a Shapiro-Wilk analysis is performed to check normality. In the case of not obtaining parametric data, nonparametric tests will be used. To evaluate and analyze the Target Path tracking and average vibration of the proposed system, we compare the root mean square errors (RMSE) of the two systems evaluated.

B. SUBJECTIVE RESULTS

1) COGNITIVE WORKLOAD

The results obtained from the NASA TLX questionnaire filled out by the ten UDEX AQP agents per item are shown in Figure 13. These items correspond to: mental demand, physical demand, performance, effort and frustration evaluated on a Likert-type scale from zero to twenty points. Mental demand in System 1 has an average of 11.1 points and in System 2 the average is 6.0 points, with a standard deviation of

5.66 and 3.33 respectively. Physical demand in System 1 has an average of 2.0 points and in System 2 it has 1.0 point, with a standard deviation of 0.66 and 0.42 respectively. Temporary demand in System 1 has an average of 6.6 points and in System 2 it has 2.5 points, with a standard deviation of 4.45 and 1.18 respectively. Performance in System 1 has an average of 5.9 points and in System 2 it has 5.0 points, with a standard deviation of 2.72 and 4.64 respectively. Effort in System 1 has an average of 9.2 points and in System 2 it has 4.9 point, with a standard deviation of 4.66 and 2.02 respectively. Finally, frustration in System 1 has an average of 9.6 points and in System 2 it has 5.2 point, with a standard deviation of 6.01 and 3.52 respectively.

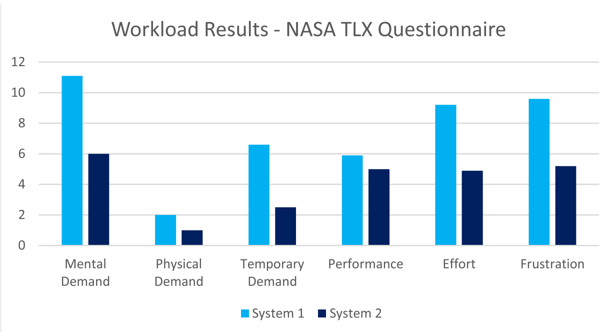

FIGURE 13. Results of NASA TLX questionnaire per item.

To evaluate the general mental workload, the data obtained from the NASA-TLX questionnaire were analyzed under the Shapiro Wilks test to evaluate the normality of the distribution, being the null hypothesis that the data do not follow a normal distribution and obtaining a significance in the case of System 1 of $p = 0.462$ and the case of System 2 a $p = 0.583$, the null hypothesis is rejected, accepting the alternative hypothesis being that the data follow a normal distribution. Subsequently, to verify the existence of a significant difference between the data obtained from the NASA-TLX questionnaire in System 1 and 2, a one-way RM ANOVA is used, obtaining a significance $p < 0.001$, demonstrating that there is a significant difference between the data obtained in System 1 and System 2. In graph X, a box plot of the variances of the results obtained from the NASA TLX and SUS questionnaires in both systems is observed. Showing a significant difference in the results obtained. A box plot of NASA TLX questionnaires results can be seen in Figure 14.

2) SYSTEM USABILITY

The data obtained from the SUS questionnaire were analyzed under the Shapiro Wilks test to evaluate the normality of the distribution, being the null hypothesis that the data do not follow a normal distribution and obtaining a significance in the case of System 1 of $p = 0.091$. In the case of System 2, a $p = 0.298$, the null hypothesis is rejected, accepting the alternative hypothesis that the data follow a normal distribution. Subsequently, to verify the existence of a significant

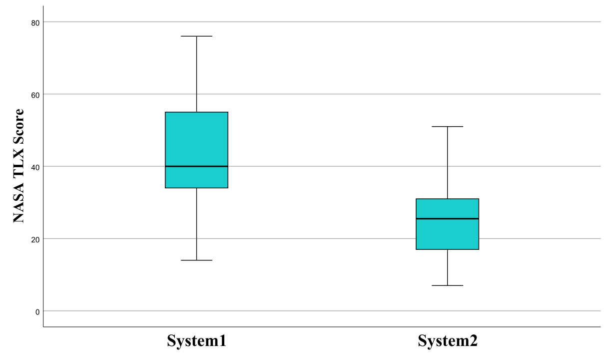

FIGURE 14. Box plot of NASA TLX questionnaire results.

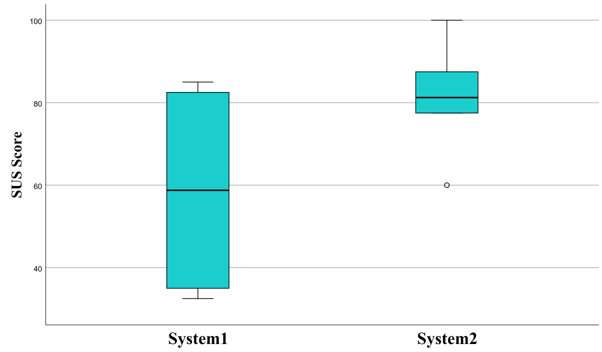

FIGURE 15. Box plot of SUS questionnaire results.

difference between the data obtained from the SUS questionnaire in Systems 1 and 2, a one-way RM ANOVA was used, obtaining a significance $p < 0.001$, showing that there is a significant difference between the data obtained in System 1 and System 2. A box plot of SUS questionnaires results can be seen in Figure 15.

C. OBJECTIVE RESULTS

1) TIME OF COMPLETION

To evaluate the times of completion obtained in the pick and place and consecutive pick and place tasks, a one-way RM ANOVA is used; however, it is necessary to first evaluate the normality of the data through a Shapiro Wilks analysis, obtaining a significance value of $p = 0.861$, 0.881, 0.792, 0.879 respectively for Tasks 1 and 2 of System 1 and Tasks 1 and 2 of System 2, verifying that the data follow a normal distribution. Subsequently, the data are evaluated by one-way ANOVA, obtaining a significance $p < 0.001$, indicating that there is a significant difference, however, to find the location of this difference between the four variables analyzed is necessary a Post-hoc analysis, determining that the significance of the paired comparisons of the variable Task 1 of System 1 with Task 2 of System 1, and Task 1 of System 2 and Task 2 of System 2, obtained the significance $p = 0.001$, 0.008, showing a significant difference in the times achieved between System 1 and System 2 in the Pick and Place and Consecutive Pick and Place tasks. In a general media comparison the completion time in System 2 has decreased in 33.03%. Figures 16-19 shows heat maps with the times obtained in the Pick and Place performance tasks with the three different objects of both Systems, showing a significant difference in the performance of System 2. Figure 20 shows a box plot showing the notorious difference in the performance of System 1 and 2 in the Pick and Place and Consecutive Pick and Place tasks.

2) TARGET PATH TRACKING

To analyze and evaluate the Target Path tracking of the proposed system is used the motion tracking algorithm, the path traced is the data evaluated, we compare the RMSE of the two systems evaluated. Figure 21 shows the target path tracking response of System 1 and System 2 obtained from the Task 1 realized for the ten agents. Table 3 shows the RMSE errors obtained in both systems, indicating that System 2 has a decrease in the Target Path Tracking error of 67.57% with respect to System 1.

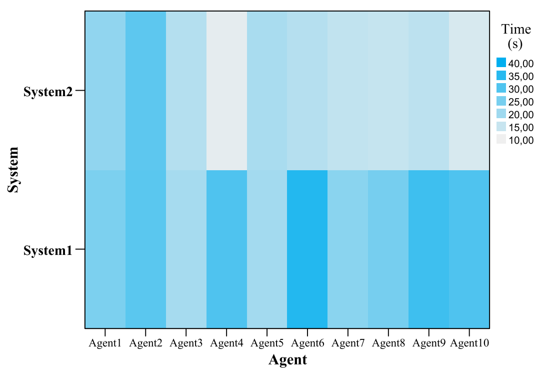

FIGURE 16. Heatmap of completion times with first object.

3) AVERAGE VIBRATION

To evaluate and analyze the Average Vibration of the proposed system, we compare the root mean square errors (RMSE) of the two systems evaluated. Figure 18 shows the target path tracking response of System 1 and System 2 obtained from the Task 3 realized for the ten agents. Table 4 shows the RMSE errors obtained from the data of Figure 22, indicating that System 2 has a decrease in the average vibration of 31.61% with respect to System 1.

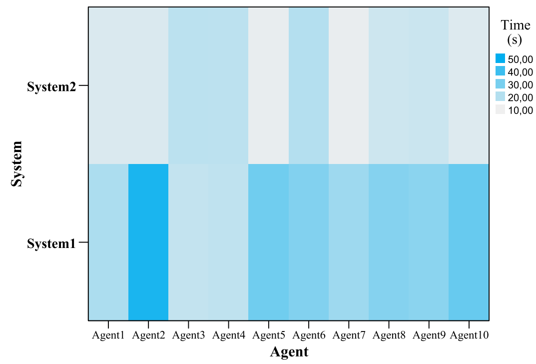

FIGURE 17. Heatmap of completion times with second object.

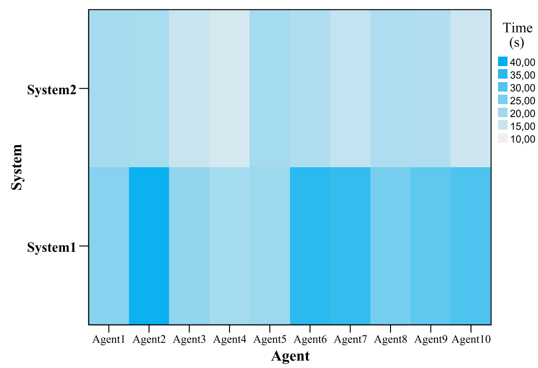

FIGURE 18. Heatmap of completion times with third object.

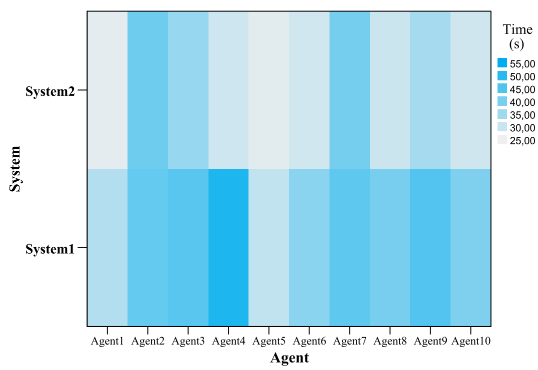

FIGURE 19. Heatmap of completion times in consecutive task.

IX. DISCUSSION

A. TARGET PATH TRACKING ANALYSIS

The results obtained in Figures 21 and Table 3 show that System 2 has an improvement of 67.57% over System 1 for the target path tracking task; Figure 21 shows graphically that using this system composed by the optimal signal processing, the trajectories obtained are much more similar and closer to the target path than the trajectories of System 1. These results validate Hypothesis 3, achieving that the robotic gripper reproduces the intentional movements of the operator when controlling the system using the LM, eliminating the system noises and the physiological tremors of the hand of the operator. This, in turn, has a positive impact on the performance of the operators when performing common tasks in EOD environments, such as Pick and Place tasks; due to a better interpretation of the intention of the operator, they achieve much more adequate control of the robotic arm without fear of making movements that destabilize the task or detach the explosive load to be manipulated.

These results indicate that Optimal target path tracking also reduces the mental workload of the operator by performing tasks with greater stability and more fluid movements without

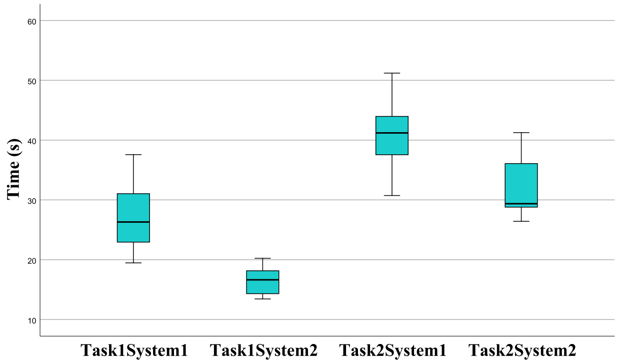

FIGURE 20. Box plot of Completion times in Task 1 and Task 2.

TABLE 3. Target Path Tracking RMSE obtained in Task 1 evaluation.

	System 1 Target Path Tracking		System 2 Target Path Tracking	
	RMSE x-axis	RMSE y-axis	RMSE x-axis	RMSE y-axis
Agent 1	0.678	1.202	0.194	0.389
Agent 2	0.729	1.091	0.126	0.379
Agent 3	0.447	1.309	0.163	0.245
Agent 4	0.859	0.974	0.257	0.365
Agent 5	0.648	0.941	0.335	0.124
Agent 6	0.575	1.183	0.314	0.138
Agent 7	0.575	0.273	0.221	0.159
Agent 8	0.648	1.275	0.237	0.348
Agent 9	0.824	0.154	0.567	0.124
Agent 10	0.495	0.979	0.177	0.173

TABLE 4. Average Vibration RMSE obtained in Task 3 evaluation.

	System 1	System 2
	Average Vibration RMSE	Average Vibration RMSE
Agent 1	0.8726	0.6902
Agent 2	1.0142	0.7246
Agent 3	0.8731	0.5021
Agent 4	0.9815	0.5669
Agent 5	0.9546	0.7153
Agent 6	0.8376	0.7082
Agent 7	0.8174	0.4084
Agent 8	1.084	0.6119
Agent 9	1.077	1.0228
Agent 10	0.9072	0.492

the need to make constant rectifications or attempts to correct the trajectory of the robotic gripper.

B. AVERAGE VIBRATION ANALYSIS

The vibration analysis shows that System 2 has an average vibration 31.61% percent lower with respect to System 1; this result provides evidence for Hypothesis 3. Specifically, our results show that the system composed of the new Optimal Signal Processing drastically reduces the vibration of the gripper due to the nature of the LM sensor, the physiological tremors, and the involuntary movements of the operator. Because each filter that makes up the Optimal Signal Processing aims explicitly to reduce a type of noise or jitter that generates vibrational movements in the robotic system, the resulting signal possesses high stability, as shown in Figure 22 and Table 4.

The results also show that incrementing the stability of the robotic gripper also positively influences the target path tracking due to the reduction of the micro-movements of the robotic gripper resulting from the physiology of the hand of the operator and the noises inherent to the operation of the LM sensor, the operators experience a fluid movement when controlling the robotic arm, even when placing their hand relatively still in the workspace the robotic gripper copies this static action without disturbances. When an intentional movement is executed, the reduction of vibration produces a stable movement of the robotic gripper to the setpoint marked by the hand of the operator also reducing the target path tracking error.

During agent testing the two systems and filling out the NASA TLX an SUS questionnaires, UDEX agents emphasized that in real EOD environments, stability is critical to ensure the safety of personnel, equipment, and nearby infrastructure.

C. TIME COMPLETION ANALYSIS

The completion times obtained in the Pick and Place or Consecutive Pick and Place task show results, that prove Hypothesis 2; specifically, it has been possible to reduce the completion time of the Pick and Place tasks using the proposed system with respect to the System 1, the performance achieved in System 2 is notoriously superior, reducing the task completion times, This is possible due to an improvement in specific aspects that were achieved, such as greater stability in the robotic gripper and an improvement in the identification of the intention of the operator, these optimized characteristics in System 2 facilitate the completion of Pick and Place tasks considerably, as shown in the heat maps in Figures 16-19.

In a real EOD environment, high task performance is necessary due to the limited time available to perform these activities. Commonly to achieve high performance, EOD robot operators need many hours of training and practice, however, this new system proposed in this paper, does not require extensive training to achieve good performance, as evidenced in Figure 16, this translates as less investment in training personnel to teleoperate EOD robots, as well as achieving that the control of these robots are no longer exclusive to highly experienced operators, but also new operators in the area of teleoperation.

D. MENTAL WORKLOAD AND USABILITY ANALYSIS

The results obtained show that the mental workload has been drastically reduced in System 2 with respect to System 1; this result is closely related to the features optimized in System 2, such as high stability and correct identification of the intention of the operator. In the same way, the usability has increased in System 2, the NASA-TLX and SUS questionnaires share similarities in the format of their questions, in most cases, an increase in the usability of the system means also a decrease in the mental workload.

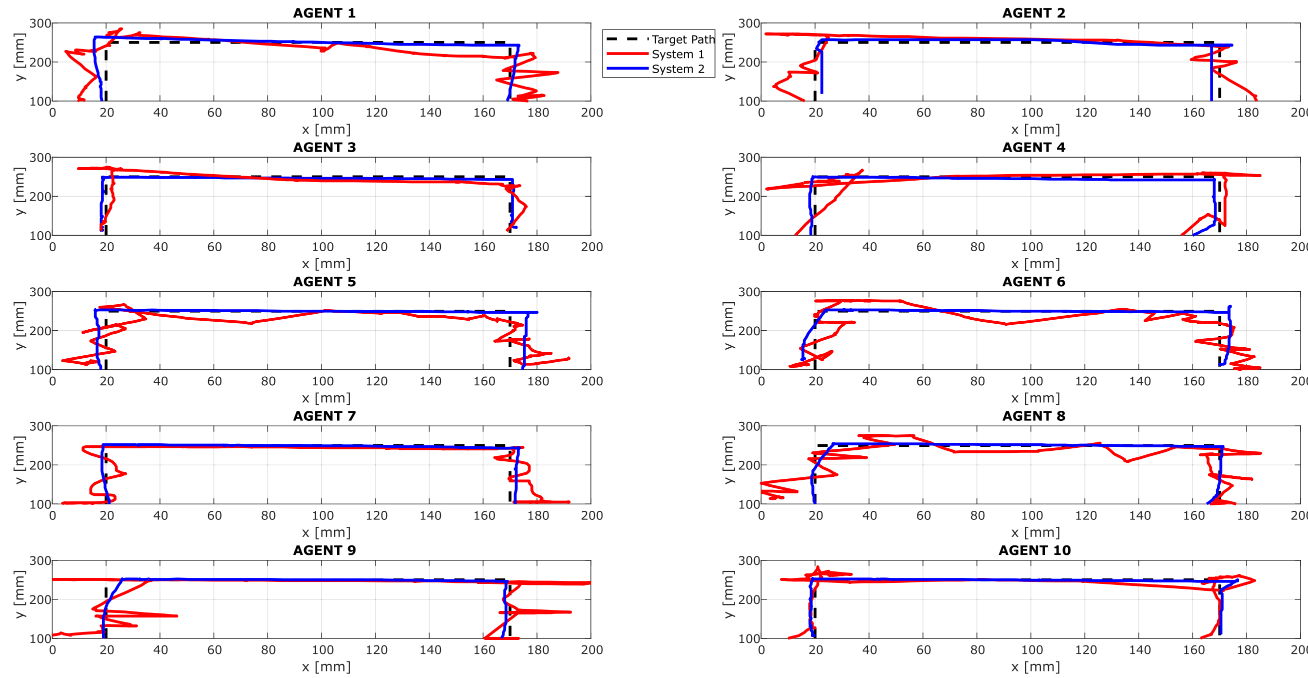

FIGURE 21. Results for the 10 agents in the target path tracking task.

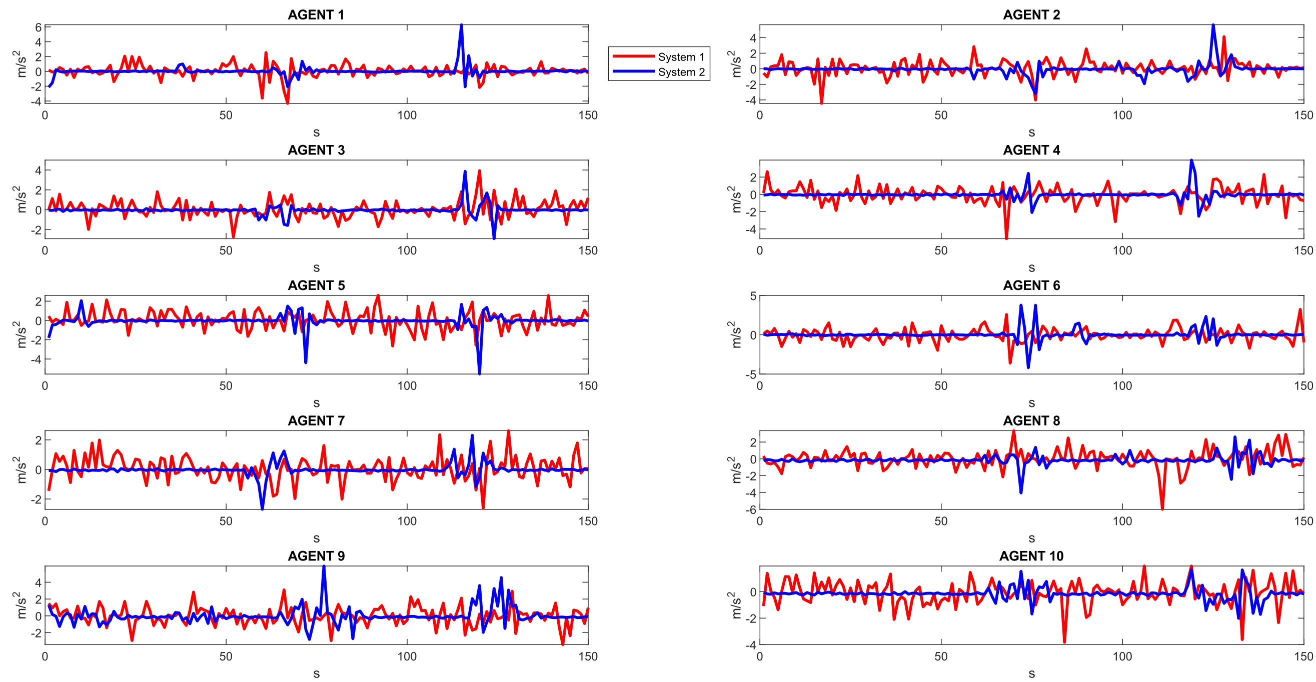

FIGURE 22. Results of the 10 agents in the gripper stabilization task.

Specifically, the results obtained in the NASA TLX questionnaire indicate a reduction in each item evaluated, even though the participants do not perceive a significant improvement in performance, the objective results prove that the time to complete the tasks was drastically reduced. Frustration and mental demand levels were also significantly reduced, demonstrating that System 2 greatly improves Pick and Place task performance. In terms of physical demand, participants report that both systems have low physical demand, this would indicate that the LM sensor is a suitable interface for controlling robotic systems as it does not require high physical effort.

The improvement in these two aspects with the proposed system is also evidenced in the results obtained in the performance of the operators in the Pick and Place and Consecutive Pick and Place tasks. This is due to greater ease on the part of the operators for the completion of tasks.

The mental workload is a determining aspect in the systems related to the teleoperated control of robots; this is due to the fact that a high mental workload implies greater difficulty and mental exhaustion when performing these tasks. On the other hand, usability is an aspect that is evaluated in the systems to demonstrate at what level users validate using these systems or interfaces. These results provide evidence of the validity of Hypothesis 1, demonstrating that not only has the mental workload and usability been maintained with respect to System 1, but that the first has been reduced and the second has increased with the proposed system.

A summary of the results of the hypotheses raised in Section IV is presented in Table 5.

TABLE 5. Summary of Hipotheses Support.

Hypotheses	Analysis Method	Support
H1: Less Mental Workload and Increased Usability	RM One Way ANOVA	Full Support
H2: Less time to complete Pick and Place tasks	RM One Way ANOVA	Full Support
H3: Less Average Vibrationin the Gripper	Average Vibration	Full Support
H4: Optimal Target Path Tracking	Average Error	Full Support

X. LIMITATIONS AND FUTURE WORK

This research has focused on implementing Optimal Signal Processing that allows the use of the Leap Motion interface for EOD applications. However, it has not yet considered some aspects that appear during the activities of deactivation of explosives with EOD robots, such as:

- The delay in robot control has not been considered; this factor is present in most teleoperated systems, it should also be considered that the cascade combination of these three filters that compose the signal processing proposed presents an additional delay that might affect the control of the robot, although this has not been evident during the tests performed.
- The tasks performed by the agents were carried out with a direct line of sight, in future research should be considered the operation by camera vision, where the greatest difficulty is the loss of depth sensation, a difficulty present in robot teleoperation.
- During the tests, the high sensitivity to light changes of the LM sensor was noticed; this should be considered in a real environment.

For future work, a new system composed of this proposed signal processing will be implemented that covers all these limitations to be used in real EOD environments.

XI. DESIGN AND RESEARCH IMPLICATIONS

The LM sensor has proven to be an efficient and low-cost solution to provide an interface to control a robotic arm; the complications derived from the use of this sensor for an EOD environment have been solved with the Optimal Signal processing, in the same way, multiple applications can be solved with this sensor using a Signal Processing suitable for each case considering the characteristics required.

The setup used for target path tracking tests, vibration tests, and performance tests was implemented without the high cost and simultaneously ensuring that the data obtained has a greater consistency. This easily implemented setup can also be used to evaluate different systems including different robotic arms.

The results obtained in this research indicate that in the case of EOD tasks, a stable system also allows higher performance in the completion of these tasks as well as in the mental workload and usability involved. Designers and researchers focusing on this environment should aim to systems that prioritize stability and robustness against physiological disturbances.

XII. CONCLUSION

This paper has presented an Optimal Signal Processing using a Leap Motion device to operate the movements of a robot oriented to EOD applications; this proposal is focused on eliminating the physiological tremors of the hand of the operator, as well as the typical noises of the sensor. Its performance has been tested through different tasks such as pick and place, consecutive pick and place, and stability, as well as performance evaluations, target path tracking, vibration, mental workload, and usability of the system. The results have been compared with one of the most commonly used signal processing in this type of system, the Kalman filter processing.

The results obtained show that the proposed system has achieved a significant improvement in terms of the stability and target path tracking of the robotic gripper, specifically, the average vibration has reduced in 31.61% and the target path tracking error in 67.57%. This optimal signal processing also has demonstrated a better performance in the tasks of pick and place performed by the agents, decreasing the average time it took them to perform these tasks in 33.03%. Tests based on NASA-TLX protocols show that the operators had a lower mental workload when using this system. At the same time, the SUS questionnaire determined higher usability of the proposed system.

These results indicate that the vibratory movements in the end-effector of teleoperated robotic systems negatively affect the performance of the operator, showing a higher cognitive load and lower usability of the system. It is also concluded that the physiological tremors of the operator have a significant impact on the vibrational movements of the end-effector, and by filtering them, considering their frequency characteristics, a sufficiently stable system for EOD tasks can be achieved.

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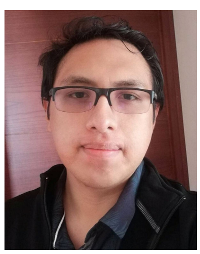

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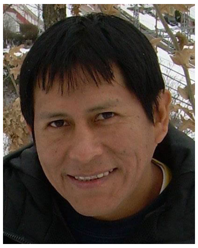
YURI SILVA VIDAL, photograph and biography not available at the time of publication.



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