Application of a Modular Wearable System to Track Workers' Fingers Movement in Industrial Environments

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***Abstract*—The growing demand for superior quality products at higher throughput rates and the constant evolution of industrial environments require an increasingly strict control over manual operations performed by workers. This paper presents a study evaluating the possibility of using a modular wearable system to track workers' fingers motion during different tasks in industrial environments. The system is composed by a series of modules with embedded sensors and electronics, each worn on a single finger, and an external data elaboration device. In order to test system performances, we simulated some actions potentially executed by workers in industrial environments. Achieved results show the system capability in discriminating between different ways of handling a tool, such as a precision screwdriver. In addition, results point out system ability in recognizing grasped objects. Finally, they highlight the possibility to identify different hand gestures to enhance human-robot interaction. System modularity permits using the lowest number of wearable modules that guarantees reliability and minimizes invasiveness at the same time.**

Keywords—finger movement tracking, wearable module, inertial measurement unit, stretch sensor, industrial environment

I. Introduction

Over the last years, we are assisting to an increasing demand for superior quality products, to be realized and distributed at higher rates [1]. Enabling contributions to achieve this goal come from automation (e.g., the growing presence of robots and cobots in assembly lines) and the combination of manufacturing world with information and communication technologies, according to Industry 4.0 paradigms [2]. This leads to the transformation of industrial environments from static and isolated manufacturing and/or distribution sites to smart factories, where Internet-of-Things and cyber-physical production systems gather information about the processes on course, with positive effects on their efficiency and, consequently, on the throughput [3]-[4].

Nonetheless, the execution of manual operations by workers remains one of the most performed tasks, for example, in situations requiring the complete process flexibility [5] or the collaboration between humans and robots in shared workspaces, such as robotic cells [6]. Furthermore, manual operations (even those repetitive) are still fundamental in semi-automated or non-automated environments [7]. Therefore, it is clear how the correctness of manual operations plays a central role among the factors affecting many industrial processes. For instance, the incorrect execution of repetitive movements in workshops, associated with individual predisposition, may cause musculoskeletal injuries indicated as repetitive motion disorders (RMDs) [8]. Another important task is the assembly of different parts composing a product. In this case, finding the right part in the warehouse and following a specified assembly order are fundamental operations, to avoid any possible mistake. This is true especially when the task becomes repetitive, as for different variants of the same product. Thus, worker knowledge about how a task has to be carried out helps reducing human errors, which may slow down the process and decrease final product quality. Finally, active collaborations between human operator and robot requires the latter to recognize specific actions performed by the former [6]. In these contexts, the possibility of having available a supervisor system that tracks worker's hand gestures (in particular, of fingers) may give an important contribution. In fact, such a system may verify whether movements are correct, guide a worker towards the right operation to be performed at a precise moment, and/or improve human/robot interaction. As an example of this interest, tracking devices have been already conceived to help identifying the right position of items in inventories [9].

Fingers motion tracking systems are currently spread, as they represent suitable solutions for different applications. Examples range from monitoring impaired people capabilities [10]-[11], to movement analysis during the execution of precise actions [12], from enhancing object design in combination with virtual reality environments [13], to the contribution in developing human-machine interfaces [14]-[16]. Such systems belong to two main groups, based on their operating principle to obtain data about fingers movement. Those from the first group rely on optical instrumentation, such as cameras and image processing algorithms. They guarantee the hand to move freely in the space, without constraints. However, achieving high performances generally means employing expensive instrumentation. In addition, industrial environments are characterized by conditions, such as changing illumination and the presence of waste and dust possibly accumulating on the lenses of cameras, which may heavily affect final results. The second group includes

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wearable devices equipped with sensors and electronics for data elaboration and transmission. These devices can be realized with low-cost components, but they must comply with workspace safety rules, be comfortable to the worker and not limit task execution because of fabrication constraints. As an example, wired solutions may not be suitable.

In previous works [17]-[18], we proposed a measurement system for tracking fingers movement. Such system is composed by different wearable modules with embedded sensors and electronics, which can be worn in a minimally invasive way, and an external data elaboration device. In this paper, we present a study evaluating the possibility of system application to industrial environments. In particular, by simulating tasks potentially performed by a worker, we aim at assessing system ability in recognizing different actions during task execution.

II. SYSTEM DESCRIPTION

The measurement system (Fig. 1) consists of two parts: 1) a wearable device for tracking fingers movement and 2) an external mobile device for post-elaborating and displaying collected data. The wearable device consists of independent and portable modules, which are positioned on thumb and index in Fig. 1a. No cables, wires or garment connect them. In this way, the measuring system is modular and more control modules may be interconnected for measuring the motion of more fingers. Furthermore, no constraints obstruct finger movements. The modules are equal and they can be adapted to any finger.

A single module measures flexion and extension of the proximal interphalangeal joint and tracks position and motion of the first and second phalanges in space. Joint movements are monitored by a commercial stretchable strain sensor for large deformation, produced by Images SI Inc. [19]. The stretch sensor is based on a conductive rubber that increases

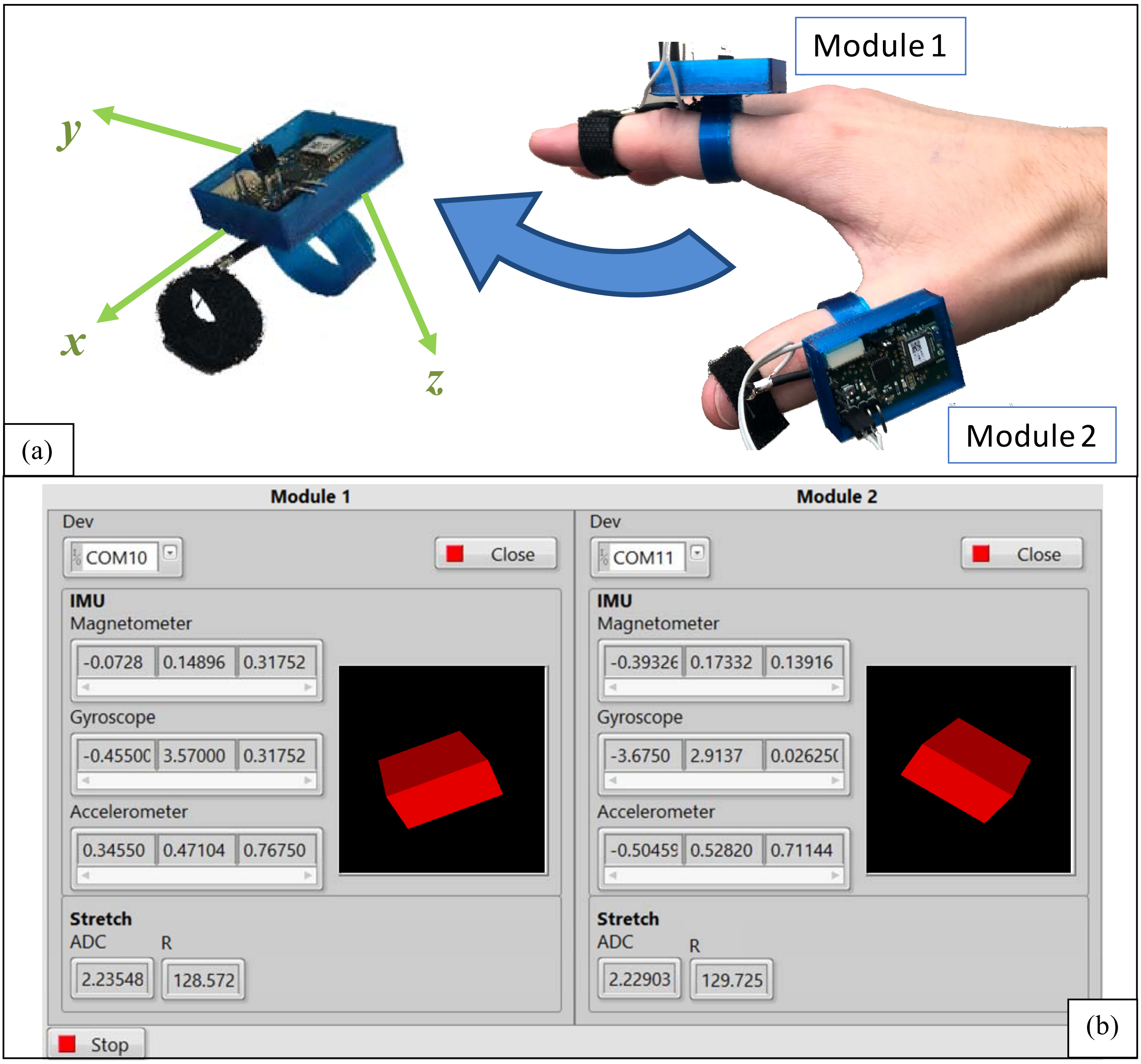


Fig. 1. Measurement system. (a) wearable device with two identical measurement modules (stretch sensor + IMU + circuit board). Module coordinate system is highlighted. (b) LabVIEW interface running on an external mobile device for data collection and elaboration via Bluetooth standard.

its electrical resistance when it is stretched. This kind of sensor is frequently used in the literature for these applications [20]. It is fixed to the finger through two rings positioned on the first and second phalanges. Then, the motion of the first phalanx is tracked by an inertial measurement unit (IMU). Therefore, considering that the second phalanx can perform only a flexion/extension movement with respect to the first one, then complete information about finger movement can be collected by IMU and stretch sensor. The IMU is single chip LMS9DS1, produced by STMicroelectronics, and includes a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer. Both IMU and circuit board are closed inside a box (36 mm x 25 mm x 10 mm) fixed on the ring of the first phalanx. The circuit board includes a conditioning circuit for the stretch sensor and a microcontroller unit for collecting and sending (via Bluetooth) the measurement data to the external device at a sample rate of 20 Hz. A 40 mAh polymer Li-ion rechargeable battery (20 mm x 11 mm x 3 mm) is placed in the box and guarantees module proper functioning, which requires 20.52 mA on average and 38 mA during data transmission for 1 ms. The total weight of a single module is 14 g. A more extended description of the module is reported in [17].

Measurement data can be received by any external device equipped with a Bluetooth Low Energy module. Data communication and elaboration are managed by the built LabVIEW Virtual Instrument (VI), which shows all data collected by IMUs and stretch sensors (Fig. 1b). It also displays IMUs orientation in the space. In this work, the VI runs on a notebook with two Bluetooth transceivers.

III. Experimental Analysis

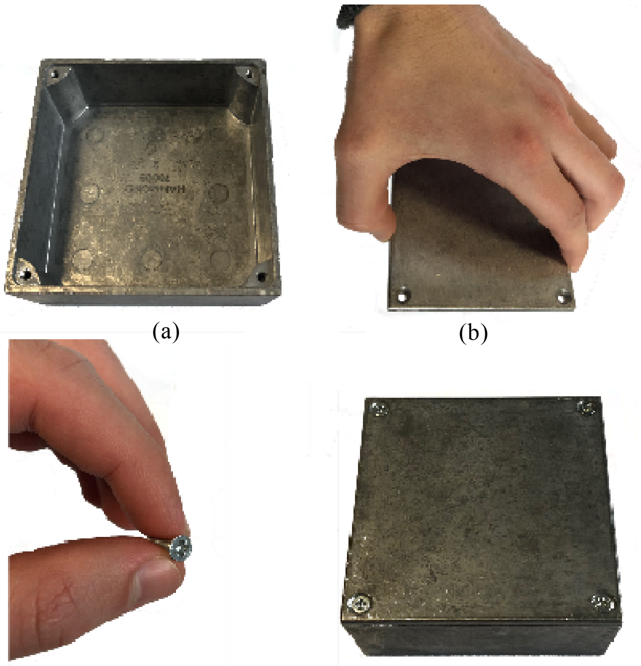
A. *Performed tests*

We carried out a series of tests, mimicking typical actions that a worker could potentially execute in different industrial environments. In this way, we evaluated system capabilities in such illustrative scenarios.

The first test permitted to monitor operator's fingers movement while performing a precision screwing operation. A male subject wore the measurement modules on his middle and thumb. Then, he repeated the screwing operation five times, by handling a precision screwdriver in the way shown in Fig. 2a (grip #1). Afterwards, he executed the same operation, but handling the screwdriver once as illustrated in Fig. 2b (grip #2) and once in the way shown in Fig. 2c (grip #3). We analysed the data obtained from each measurement module and fused them to discriminate between the movements derived from the three different grips, taking grip #1 as reference for the comparison.

(a) (b) (c)

Fig. 2. Different grips when handling a precision screwdriver during analyzed screwing operation. (a) grip #1. (b) grip #2. (c) grip #3.



(a) (b) (c) (d)

Fig. 3. Assembly scheme of the box. (a) the container is automatically supplied. (b) lid grasping. (c) screw grasping. (d) assemblied box.

The second test aimed at assessing the system ability in recognizing which object is grasped when the operator is required to assemble a box consisting of a container, a lid, and four screws to fix the two parts. The assembly scheme is graphically explained in Fig. 3. The operator has to secure the container (Fig. 3a), by collecting the lid (Fig. 3b) and the four mounting screws (Fig. 3c), in order to complete the task (Fig. 3d). Measurement modules were worn on the index and thumb by a male subject, who grasped and released the lid multiple times in a repetitive way. Then, he repeated such operation with one of the screws. Again, we combined the data coming from the sensors present in each module, in order to perform this type of recognition.

The third test is a preliminary study about the identification of a simple and reduced gesture set. As the measurement module is able to recognize hand orientation and the flexion angle of the first phalanx, it can also be used to discriminate different hand poses (Fig. 4). In fact, in an industrial environment, these gestures might be associated to some actions carried out by a robot/cobot. During the test, the system was worn on the thumb and index by a male user, who performed the following movements involving the hand poses represented in Fig. 4. Movement M1 is between positions (0)

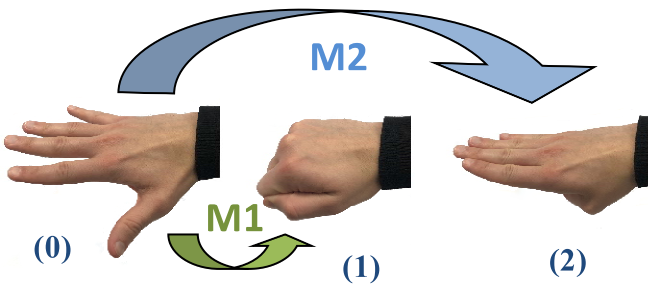


Fig. 4. Hand poses chosen for gesture recognition function. Pose (0) is used as a reference of no gesture, (1) and (2) are the positions to be recognized.

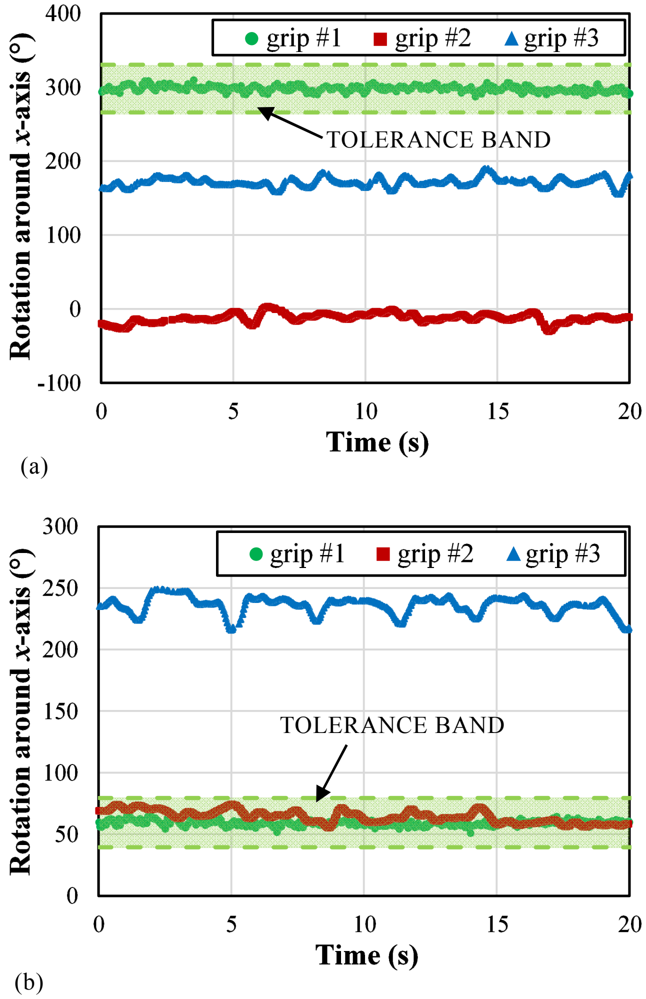


Fig. 5. Angle of rotation around x-axis as a function of time, corresponding to the grips analyzed during the execution of a precision screwing operation. (a) thumb. (b) middle.

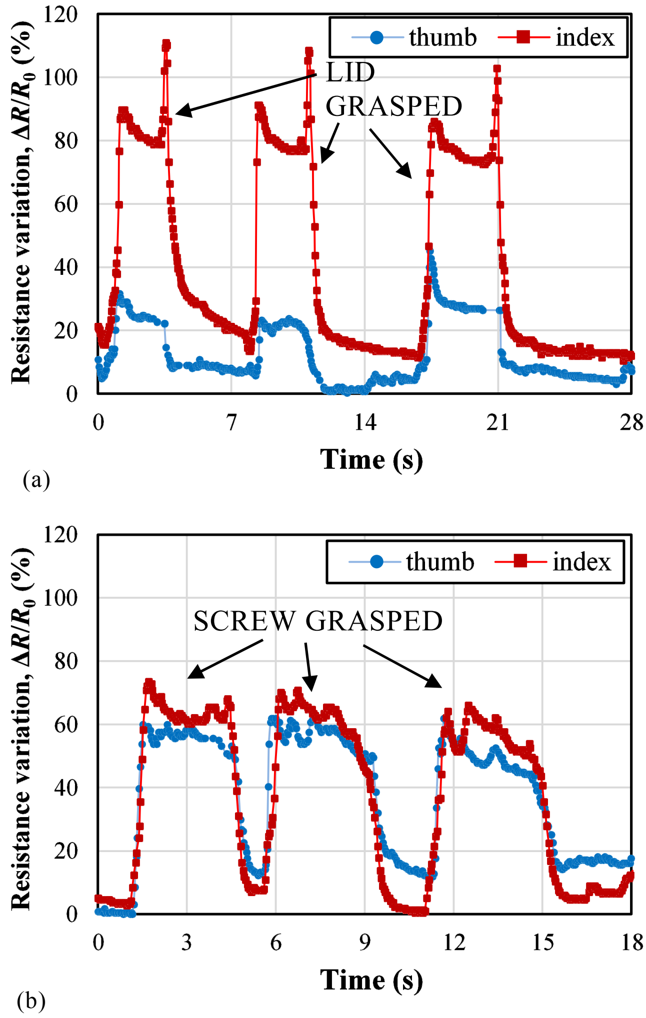


Fig. 6. Variation of stretch sensor resistance as a function of time for thumb and index, when different objects are grasped. (a) lid. (b) screw.

and (1); movement M2 is between positions (0) and (2). Pose (0) was exploited as a default base position, whereas the others had to be actively recognized. Movements were repeated five times each.

B. Results

As one of the parameters for movement discrimination, in Fig. 5 we show the time trends characterizing the angle of rotation around x-axis of module coordinate system, both for thumb (Fig. 5a) and middle (Fig. 5b). Each trend corresponds to the movement generated when precision screwdriver was handled in the ways shown in Fig. 2. We determined angle values by following established techniques known from the literature [17]-[18]. The repetition of the movement with grip #1 permitted to identify a tolerance band for the rotation angle, which is equal to 64° for thumb and 40° for middle. This band contains all values corresponding to such movement with a 95% degree of confidence. Therefore, it helps discriminating whether screwing operation is being performed with grip #1. In fact, angle trends related to other grips are out of the band, as it happens for grip #2. Furthermore, combining data from the two fingers augments results reliability. The case of grip #3 is a clear example. In fact, the trend for the middle lies entirely inside the tolerance band, but, at the same time, the one related to thumb is completely out. Gathering data from other fingers through additional wearable modules would even ameliorate the outcome of this analysis.

Fig. 6 reports the variation of stretch sensor resistance R as a function of time, for both thumb and index, when lid (Fig. 6a) or screw (Fig. 6b) are grasped. Stress relaxation behavior is visible and this is a common behavior well described in the literature for strain sensors [21]. In this application, such behavior has negligible effects on the resistance variation due to the movement. This variation is represented as percentage with respect to resistance R_0, corresponding to the case in which fingers are extended and are grasping no objects. The value of R_0 is equal to $(118 \pm 3)\,\Omega$ for thumb and $(135 \pm 2)\,\Omega$ for index, respectively. Reported graphs highlight that $\Delta R/R_0$ response is strongly dependent on grasped object, looking in particular to the peak plateau levels. In fact, as expected, different object sizes cause different bending degrees of the phalanges. In addition, the combination of the values obtained from the two measurement modules enhances object identification. For example, when the screw is grasped, peak plateau levels for both fingers are close to each other, lying between 50% and 70%. On the other side, they are completely different in the case of the lid, being between 20% and 30% for the thumb and around 80% for the index. Therefore, stretch resistance

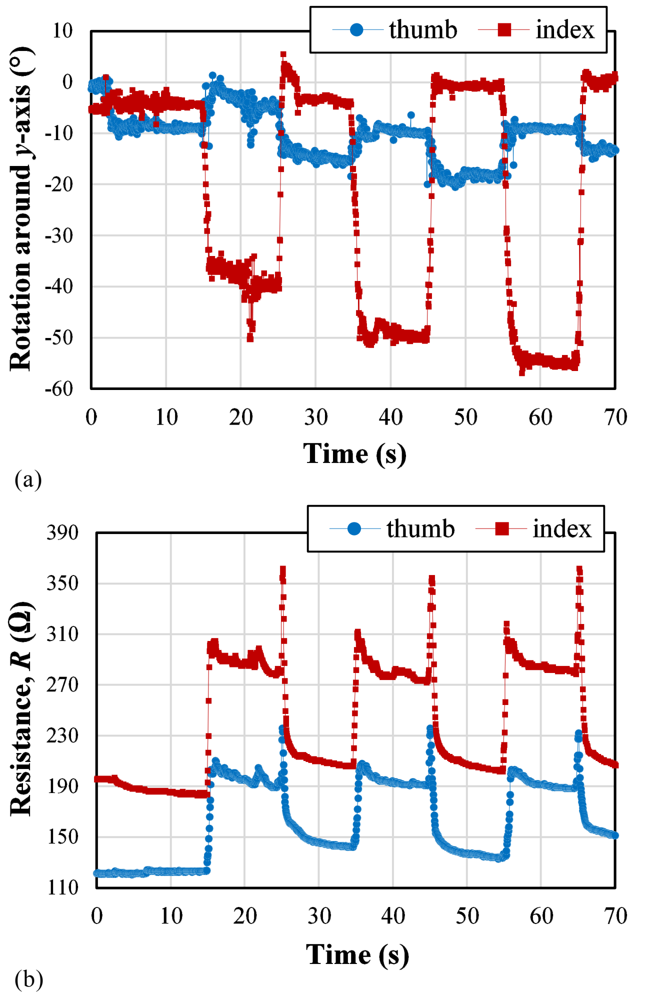


Fig. 7. Results for thumb and index during movement M1. (a) angle of rotation around y-axis. (b) stretch sensor resistance.

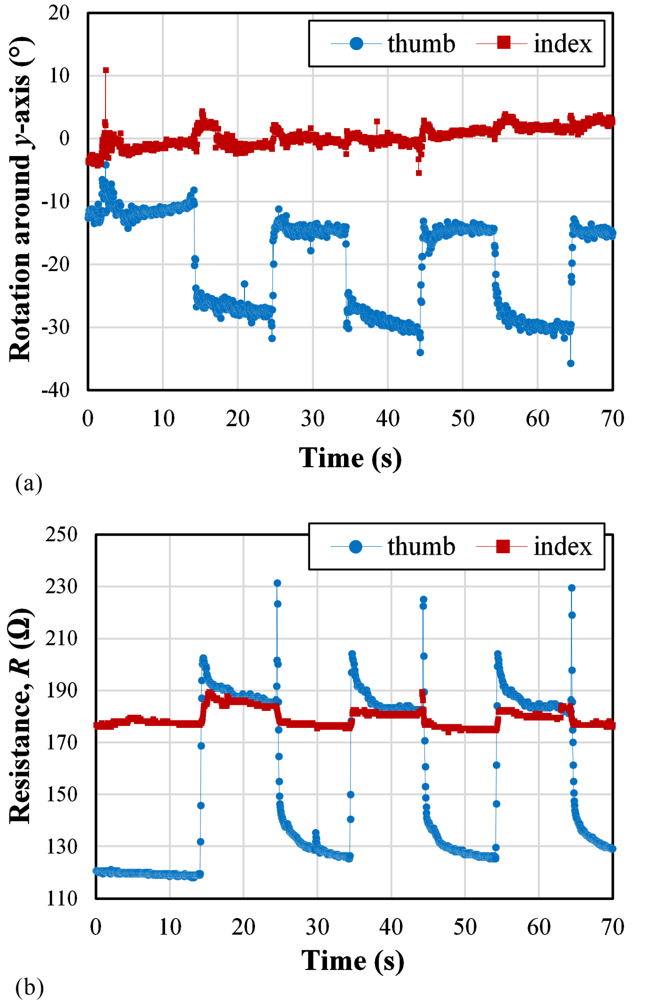


Fig. 8. Results for thumb and index during movement M2. (a) angle of rotation around y-axis. (b) stretch sensor resistance.

variation is a useful indicator for object recognition, especially if data are collected from multiple fingers.

Results from the third test are arranged in Fig. 7 and Fig. 8, for movements M1 and M2, respectively. Fig. 7a and Fig. 8a report the rotation angle around y-axis, whereas Fig. 7b and Fig. 8b represent stretch sensor resistance R, as a function of time and for thumb and index. To get better graphic results, only three of five repetitions of the same movement are shown. The hand poses are recognized analyzing the data. Movement M1 is associated to a complete index flexion and a partial thumb flexion. This is reflected in the variation of the observed parameters with respect from pose (0). In fact, the angle of rotation presents a variation for the index five times greater than the one characterizing the thumb. Also R increase is higher for the index, on average. On the other side, movement M2 implies a complete thumb flexion (R increase equal to 42%, angle decrease around 20°), whereas the involuntary movement due to anatomical constraints is just observed for the index. If crossing the analysed parameters, all these poses are non-overlapping, permitting to discriminate between different gestures.

IV. Conclusions

In this paper, we presented a study to evaluate the application of a finger tracking system for monitoring the tasks performed by workers in industrial environments. The system is composed by wearable modules with embedded sensors and electronics and an external data elaboration device. After having illustrated system fundamental characteristics, we described the tests through which we evaluated its performances. In particular, we mimicked some actions that a worker has potentially to execute in an industrial environment. Finally, we showed the obtained results. First, they highlight the capability of the system in discriminating between different ways of handling a tool, such as a precision screwdriver. Then, they point out system ability in recognizing objects when they are grasped. Finally, they show the possibility to identify different hand gestures. Furthermore, collecting data from more than one finger simultaneously increases system reliability.

Presented study suggests that the measurement system could be potentially employed to track workers' fingers motion and orientation, in order to evaluate if workers are carrying out a task correctly. For instance, it could inform workers in real time if they are handling a tool incorrectly, or in case of wrong movements that could lead to RMDs when repeated. As an alternative, given a specified assembly order of parts, it could warn a worker when a wrong part is being grasped. In addition, it could be employed to control the movement of robots in shared workspaces or, in general, it could enhance human/robot interaction. System modularity allows using the lowest number of wearable modules that permits to track workers gestures correctly, minimizing module invasiveness at the same time. Then, the system could be connected with other devices, robots, or machines present in the factory, allowing information exchange in compliance with Industry 4.0 principles.

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