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An investigation on the usability of the Kinect by Microsoft in upper limb rehabilitation after stroke

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Director: Prof. Leonardo Pagnotta

Supervisor: Prof. Gianluca Gatti

PhD student: Giorgia Lupinacci

Abstract

Stroke is the second leading cause of disability in Europe, and the sixth leading cause worldwide. The brain damage that follows a stroke can cause the loss of upper-limb mobility, reducing the independence of people in daily life activities. Neurorehabilitation and advanced technologies propose new solutions that can induce neuroplasticity by motor learning and motor control. An example is the application of virtual reality to stimulate functional and correct motions.

In this thesis the applicability in upper-limb rehabilitation of a commercial depth sensor, the Kinect for Windows, is investigated. It was used to analyze the performance of subjects executing upper-limb rehabilitation and to allow the interaction with a virtual environment. Tests with healthy subjects and with patients were conducted.

First of all, the accuracy of the Kinect sensor v2.0 was evaluated and the performance of the sensor placed in different positions and orientations was tested. The results obtained in this preliminary study, were confirmed by the accuracy of a posture classification model, trained using the tracking data of a Kinect sensor. Finally, a system for the development of rehabilitative video-games was described. The system uses the Kinect sensor to allow the interaction with a customizable virtual environment and has the advantage to be highly flexible and patient-oriented.

The Kinect sensor offers a good compromise between accuracy and usability, and the studies conducted highlight the potentialities and limits of the sensor. Clinical trials will be necessary to obtain evidences on long-term rehabilitation.

Sommario

L'Ictus rappresenta la seconda causa di disabilità in Europa e la sesta nel mondo. Il danneggiamento del tessuto nervoso, a seguito di Ictus, può portare ad una perdita della mobilità dell'arto superiore, limitando così l'indipendenza del soggetto nello svolgimento delle normali attività quotidiane. La Neuro-riabilitazione e le tecnologie avanzate propongono nuove soluzioni, per promuovere la neuro-plasticità attraverso l'apprendimento e il controllo motorio.

In questa tesi si e studiata l'applicabilità di un sensore di profondità commerciale per la riabilitazione dell'arto superiore, il Kinect for Windows. Il Kinect e stato adottato per analisi delle performance di soggetti e come strumento per l'interazione con un ambiente virtuale. Sono stati eseguiti test con soggetti sani e pazienti.

Innanzitutto, si e effettuata una valutazione dell'accuratezza del Kinect v2.0, nonché del comportamento del sensore se posizionato in diverse posizioni e orientamenti. I risultati ottenuti in questa prima fase di studio hanno trovato conferma nell'accuratezza del classificatore di postura, il cui training è stato effettuato con dati ottenuti da un Kinect v2.0.

Infine, si è realizzato un sistema per lo sviluppo di video-games riabilitativi. Il sistema prevede l'utilizzo di un Kinect per l'interazione con un ambiente virtuale personalizzabile e ha il vantaggio di essere flessibile e altamente orientato-al-paziente.

Il Kinect rappresenta un buon compromesso tra accuratezza e utilizzabilità, e il percorso seguito ha consentito di mettere in evidenza le potenzialità e i limiti di questo strumento. Per la valutazione degli effetti a lungo termine sul recupero della mobilità, sarà necessario eseguire opportuni test clinici.

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Introduction

Stroke has high incidence in all industrialized countries and the recovery of upper limb mobility is fundamental in people affected by stroke [1]. It guarantees higher autonomy performing daily life activities, that can be traduced in a better life for patients and their caregivers.

The increasing number of people affected by stroke, the costs for health systems due to this pathology and new evidences in neuroplasticity[1], motor learning and motor control, lead scientific community to study new rehabilitative approaches [2], [3]. Combining the knowledge of experts from clinical and from technological fields, emerging and new exiting solutions can be introduced in physical therapy and rehabilitation.

The potentialities of advanced technologies, as robotics and virtual reality, are huge, and a wide range of applications is possible. However, the affirmation of new applications in physical therapy and rehabilitation, as in all the biomedical fields, is complex. To this complexity contribute: the multidimensionality of the problems, the multidisciplinary, resistances in the organizations and in the professionals that is supposed to use the new systems. The innovation process in medicine means efficacy, effectiveness, affordability, sustainability, equity, usability, market potential and accessibility [4]. All these elements represent, at the same time, a complication and a challenge for researchers.

The objective of the PhD program, discussed in this thesis, was to study the state of art in upper limb rehabilitation of post-stroke patients, and to focus the attention on a specific technology, highlighting advantages and disadvantages. In particular, the effectiveness of a motion capture device, produced by Microsoft, the Kinect for Windows [5], was evaluated.

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[1] The term Neuroplasticity indicates the "brain's ability to reorganize itself by forming new neural connections throughout life. Neuroplasticity allows the neurons (nerve cells) in the brain to compensate for injury and disease and to adjust their activities in response to new situations or to changes in their environment" [130]. The term was introduced by polish neuroscientist Jerzy Konorski in 1948 [131].

The Kinect sensor is a well-known device, firstly used in gaming, that has been adopted in several other fields because it is not expensive, easy to use and has a large applicability. This device seems to be a good compromise in terms of affordability, sustainability, usability and accessibility, and has an interesting market potential. Its efficacy and effectiveness have been studied during this PhD program, offering a contribution to knowledge about the application of Kinect sensor in upper limb rehabilitation.

An analysis of the performance of the Kinect sensor allowed to better understand the usability of the sensor for the tracking of upper body, with particular attention to upper limb. The application of the sensor in two different contexts was then proposed. In the first case the sensor was used to monitor the posture of people executing upper limb rehabilitation. In the second case, the Kinect sensor was used to develop a system for the patient-oriented rehabilitation using virtual reality.

This dissertation is structured as follows:

- In Chapter 1 the recovery of the arm motion after stroke is discussed. First of all, a brief definition of the disability is presented. Thereafter, an introduction to the main technological approach to the recovery of motor function in post-stroke patients is discussed. The attention is focused on the systems dedicated to motor learning, to robotic devices and to the application of virtual reality;
- In Chapter 2 the upper limb kinematics will be briefly discussed, then, several types of motion tracking systems are introduced. In particular, devices generally adopted for gaming, and recently popular also in rehabilitation, are described in order to understand the choice to adopt the Kinect sensor for the development of the study presented in this thesis. In conclusion, how the Kinect sensor works is discussed;
- In Chapter 3, in order to evaluate the usability of the Kinect sensor in the upper limb rehabilitation field, a comparison with a marker-based system is presented. The upper limb motion is specifically considered and the performance on its detection and tracking is evaluated. The effect of the relative location between the Kinect and the observed subject is also investigated through experimental tests performed in different configurations;

- In Chapter 4 a posture and upper limb monitoring tool is described. The work is part of a main project developed at the Intelligent Assistive Technology and Systems Lab – IATSL (Toronto Rehabilitation Institute, University of Toronto) under the title of Development of an Upper Limb Haptic Robotic Rehabilitation System for Stroke Rehabilitation. A period of seven months (January 2014 – July 2014) has been spent at the IATSL;
- In Chapter 5 a system composed by one personal computer, two screens, a Kinect™ sensor and a specific software developed here for the design of the video-games is described. The system has been tested with the collaboration of three therapists and six patients, and two questionnaires were filled in by each patient to evaluate the appreciation of the rehabilitative sessions. The tests were executed at the Associazione Nazionale Mutilati e Invalidi Civili - Riabilitazione of Crotone (Italy);
- In Chapter 6, conclusions are reported.

Chapter 1.

Upper Limb Rehabilitation after Stroke

Approximately 15 million people worldwide have a stroke each year [6]. Stroke is the second leading cause of disability in Europe, and the sixth leading cause worldwide [1]. More stroke survivors have difficulty with arm movement or are unable to use one arm in the long term, thus they are left dependent on others for everyday activities. To maximizing the participation of people with stroke in the community, rehabilitation activity since acute phase of care is necessary. The first aim of rehabilitation practice is the recovery of Activities of daily living (ADL), for example reaching, eat with spoon, wash axilla, lift a light bag [7]. In the last years scientists highlight the importance of motor learning in rehabilitation. The patients relearn how to complete a movement. In this context motivation and attention are important elements to improve patients' ability [8]. Feedbacks that give information to the patient on the quality of his performance are useful to improve motivation and quality of execution.

There is not a standard rehabilitation program. In fact, post-stroke characteristics vary between patients and over time [9]. Interventions which can be used routinely include: constraint-induced movement therapy in selected people, repetitive task-specific training and mechanical assisted training. Together with the above listed interventions, the following can also be used in addition: mental practice, EMG biofeedback, electrical stimulation, mirror therapy and bilateral training [9], [10], [11]. The evaluation of parameters that indicate evolutions in patient ability is necessary, to create a therapy that can be adaptable at the specific conditions. Technology is a key factor in the new approach to rehabilitation. It has to offer effective, easy to use and not expensive solutions. One of the last trend is the development of automatic systems, that can be used at home, autonomously by the patients, that guarantees the opportunity to increase the time dedicated to rehabilitation, reducing the health care costs [12] [13] [14]. The role of the therapists is still important, but the scientists propose intelligent systems, that can substitute the human therapists in order to offer more assistance to the patients. For an efficient design of these new products, researcher, therapists and patients have to collaborate, defining features of the new tools that can be generally accepted. Robotic devices and systems based on the virtual reality are largely proposed, but their functional benefits are not completely investigated [9].

1.1 Post-Stroke effects on upper limb

Stroke is generally defined as a neurological deficit attributed to an acute focal injury of the central nervous system by a vascular cause [15]. It is one of the main causes of disability in the industrialized countries. The upper limb (UL) impairment involves about 70% of subjects interested by stroke and only a minimal percentage of these subjects presents a recovery of the motor functions [16]. UL impairments consist of paresis, loss of fractional movement, abnormal muscle tone and/ or changes in response by the somatosensory system. All of these impairments are due to a damage of specific parts of motor cortex and can occur in combination. The most common is the paresis, where the damage to specific parts of motor cortex is the cause of a poor or absent coordinated control of muscles and sets of muscles. The results are weakness and slower, not accurate and not efficient movements. Depending on the severity of paresis, the individuals may show normal or near normal movements (mild paresis) or they can be not able to move at all (severe paresis). The paresis will interest the side of the body that is contralateral to the lesioned brain side [17], [18].

Obviously, the UL is strongly involved in the normal execution of ADL, so the loss of ability controlling the UL motion has a high impact on the life of individuals, families and on healthcare system. The rehabilitation of post-stroke patients is important in order to reduce the load attributed to these subjects. The first step of the recovery process, is the evaluation of the severity of paresis, that is done at three or more weeks post-stroke. Initial severity and rate of change of severity determine the ability of the individual to recover the motor function. The objective is to guarantee the capacity to perform activities with the UL.

Recovery of the motion can be assessed using performance measures or self-reported measures [17]. The performance measures are tests executed by the therapists and return a score that quantify the ability of the individual. Some example of these tests are the Action Research

Arm Test (ARAT) [19], the Box and Block Test (BBT) [20] and the Wolf Motor Function Test (WMFT) [21], and consist of a series of actions that the clinician asks the patients to perform. Instead, the self-reported measures consist of a set of questions that the patient have to answer, relative to the normal execution of ADL [17].

1.2 Recovery of upper limb motion: brain reorganization and motor learning

Depending on the nature, location and size of the lesion, the condition of the patient before the stroke and the time post-stroke, the disease may present in several ways. In fact, stroke is a really heterogeneous disease that does not affect only the motor function, but at the same time the cognitive, sensorial and somatosensory system. For this reason, the rehabilitation approach has to be individualized.

Furthermore, the ability of adult brain to reorganize themselves to recover loss functions, make the post-stroke rehabilitation more interesting. Damaged neural circuits can be substituted by novel circuits that activate the same or similar pattern of muscles [8], [17], [18]. Here is the substantial difference between recovery and compensation of movements. The first one happens when the damaged neuronal circuit is substituted by a new one that activate the same path of muscles. The compensation consists of the activation of neural circuits that activate alternative muscles in order to complete the same goal [8]. These compensatory strategies can allow just a partial recovery, with consequent atypical behaviors. At the same time, compensation can be part of a motor learning process.

The term *motor learning* refers to acquisition of skill, motor adaptation and decision making process oriented to the selection of the correct movement in the proper context [8], [22]. In order to stimulate the motor learning, the tasks must be variable and randomly scheduled, to induce the learner to look at the movement as to a problem that has to be resolved. Furthermore, several types of feedback can be used to induce motor learning. Verbal suggestions, visible information or mechanical stimulus are just few examples of the different kind of feedbacks that can be used with the aim to permit the patient to learn if his motion is correct or not [23]. The generation of automatic feedbacks requires the control of the motion and the availability of systems that generates the signals.

1.3 Systems and methods for upper limb rehabilitation

The rehabilitation model proposed by neuroscience, founded on the motor learning phenomenon, is the base of new approaches to post-stroke rehabilitation [11], [9]. The classical rehabilitative therapy, based on the repetition of the same movement, that was the starting point of the first robots for rehabilitation (i.e. the MIT-MANUS [24]) are called into question [9]. It has to be considered that motivation and attention are necessary, in order to induce the motor learning process.

In this context several rehabilitative systems have been realized, but there are not enough evidences on the efficacy of these approaches. More clinical tests must be finalized to the evaluation of long term efficacy of new rehabilitative systems.

The interest of researchers oriented to the development of new systems for the rehabilitation of UL post-stroke, is focused on some specific category of methods and technologies: constrain-induced movement therapy, repetitive task-specific training, robotic assistive devices, Motor Imagery and Mental practice, control strategies and the application of virtual reality [11].

1.3.1 Constrain-induced movement therapy

In the constraint-induced movement therapy (CI therapy) healthy hemisphere is constrained. This therapy induces plasticity in the damage hemisphere, forcing post-stroke patient to use paretic limb [25], as in Figure 1.1. CI can be accessible to a small percentage of patients, but introduce significant improvement in arm function [10]. In this approach the motor learning process is highly involved and the results proposed by the application of this technic suggests the effectiveness of the motor learning model [18].

Figure 1.1 Constrained-induced movement therapy.

1.3.2 Repetitive task-specific training

Repetitive task-specific training consists in the repetition of specific movements over and over again with the help of a therapist or devices. Usually these movements are necessary to complete activities of daily life. French et al. [26] present a review to examine effectiveness of this therapy and they found no evidence of significant benefit from repetitive training of upper limb functional activity. Indeed, the variability of the tasks is fundamental for the acquisition of a motor skill that the patient will be able to adapt in general situations [23].

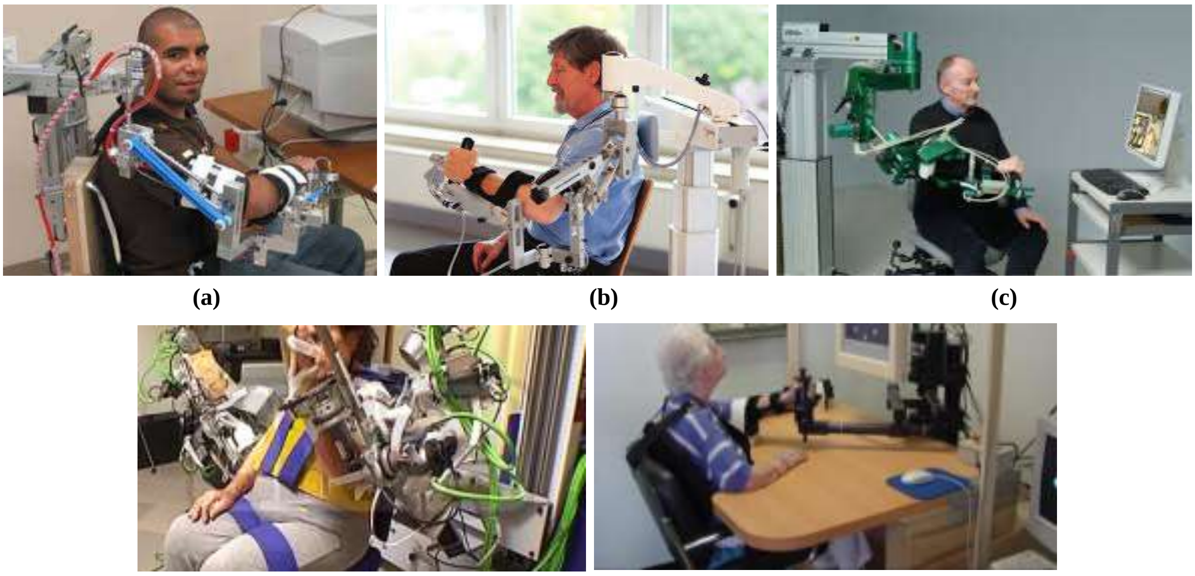
1.3.3 Robotic assistive devices

Several technology-based approaches for stroke rehabilitation exists and many robotic assistive devices have been proposed. They appear to be useful to realize training protocol with good accuracy, replication and congruity with residual ability of patients. The upper limb rehabilitation robots can be classified as exoskeleton robots and end-effector robots. A short description of these classes of systems is discussed below, to understand what are the technological methods actually adopted and what is their effectiveness in the upper limb rehabilitation, thus motivating the objectives that will be indicated.

The first class of device presented are the exoskeletons. Exoskeletons are robotic systems with a structure that reproduces human upper limb, have joint axes that match the upper limb joint axes. Exoskeletons are designed to be attached at upper limb and register movement, posture and torques applied to each joint. Thanks to mechanical structures with a number of degrees of freedom (DoF) that permit execution of the tasks in the entire range of motion of the human upper limb, it is possible an optimal control of the arm and wrist movement. At the same time, they can reproduce a trajectory previously registered and guide the patients into the execution of a specific movement [27]. This type of devices requires frequent maintenance, they are difficult to transport to the patient's home and are very expansive. In this category of robotic systems there are T-WREX [28], showed in Figure 1.2 (a), a passive system with five degree of freedom commercialized as the Armeo therapy system by Hocoma (Figure 1.2 (b)), A.G, in Zürich, ARMin III [29] (Figure 1.2 (c)), an active robot with six DoF developed at the Swiss Federal Institute of Thecnology, Zürich, and ARAMIS (Automatic Recovery Arm Motility Integrated System) (Figure 1.2 (d)), realized at the S. Anna Institute and RAN (Research on Advanced Neuro-rehabilitation), Crotone [30]. No clinical data is available for exoskeleton and actually these devices are used mainly to research into kinematics and dynamics of the human body [27], [31].

More clinical results are available for some of the end-effector robots. In this case interaction between patients and machine is limited to the end-effector. Usually end-effector robots permit movements in a plane. An example is the MIT-MANUS (Interactive Motion Technologies Inc., Cambridge, Massachusetts, USA) [24] (Figure 1.2 (e)), 2-DoF robot, used for reaching tasks in horizontal plane.

The robot sensors permit continuous measurement of position, velocity and interaction forces. Another example is the 2-DOF planar haptic interface, developed by the Intelligent Assistive Technology and Systems Lab – IATSL (Toronto Rehabilitation Institute, University of Toronto) in collaboration with Quanser Inc. [32].



(a) (b) (c)

(d) (e)

Figure 1.2 Robotic assistive devices. (a) T-WREX; (b) Armeo therapy system; (c) ARMin III; (d) ARAMIS; (e) MIT-MANUS.

There aren’t significant effects of robotic intervention on motor recovery [10] and researchers look at the application of task-based exercises like promising approach in post-stroke rehabilitation [27]. The support of games based on physiotherapy principles can be useful to motivate and to help patient to understand what is the utility of a task [33]. The robots offer the opportunity to monitor the performances of the patients and at the same time to induce the execution, automatically, of exercises with high variability and respecting the ability of the patient [8].

1.3.4 Unimanual versus Bimanual robots

Previously cited systems (T-WREX [11], ARMin III [29], MIT-MANUS [24]) and many other mechanical devices for upper limb rehabilitation, allow motion only of the impaired arm. For this reason, are defined unimanual robots. Most activities of daily living are bimanual and require coordination and control of both arms, thus in recent years there is an increasing interest for bimanual training [34], [35].

Figure 1.3 BATRAC system.

The aim of these systems is to propel paretic limb during complex movements. An example is the Bilateral arm training with rhythmic auditory cueing (BATRAC), showed in Figure 1.3, that permits to move both upper limbs simultaneously or alternatively, at a frequency paced by a metronome providing auditory cues [35]. Bilateral upper limb training offers evidences in motor recovery [36], but need more clinical results to verify effectiveness of this therapy [9], [34].

1.3.5 Motor Imagery and Mental practice

The study of brain activity and adaptability offers interesting therapeutic opportunities. Examples are Motor Imagery and Mental Practice, two techniques for the stimulation of brain plasticity. The subject imagines to execute a movement without really move the body. These techniques are used for motor recovery or to improve performances of athletes [20] and there are positive results in motor recovery [10].

A specific therapy that use Mental Practice theory is the Mirror therapy [11], [37], [38] which consists in creating the illusion of perfect bilateral synchronization, as showed in Figure 1.4. The patient executes a movement whit both arms but he may not see the paretic limb. With the use of a mirror, or with other systems, he can perceive the movement of the non-paretic limb like executed by the paretic limb too.

Figure 1.4 Mirror therapy.

1.3.6 Control strategies and motion tracking devices

Robotic systems produce information about quality of execution that the patient and therapist can visualize in real time and can be used to produce a feedback in order to stimulate the executor. There has been a progression in the development of control strategies to evaluate how robot interact with patients [39]. The role of robotic therapy control algorithms today is to tie up technological features of the robot and neuroscience theory. In fact, systems that can produce exercise for improvement of neuro-plasticity and motor recovery are necessary. Many proposed robotic systems are rigid, impose repetitive movements on planar trajectories and the patient cannot configure this movement in real application. The assist-as-need (ANN) rehabilitation paradigm propose robotic systems that are more flexible or adjustable to patients' needs [8], [23].

The control of motor activity can be done starting from the output of several types of sensors. One of the most important information used to evaluate the performance of the patient, and then to decide how to adapt the exercises, are the kinematic information of body components, returned by motion tracking sensors. These sensors do not have to necessarily be integrated in a robotic system. For example, wearable sensors for motion tracking are becoming popular, thanks to the rapid development of microelectronic, micromechanics and integrated optics. Their use is not limited to rehabilitation field, but is extended to daily life [40]. One of the most common sensor used to monitor the motion of a person, during rehabilitation or not, is the accelerometer [41]. Also optical sensors are used, in laboratory and at home, to track the motion of one part or of the entire human body. An example is the Kinect by Microsoft [42], showed in Figure 1.5 (a), a device composed by a color camera and a depth sensor that permits a marker-less motion tracking of up to six people. It is used in gaming, but is highly adopted also in rehabilitation [43].

The data recorded by the sensors are used to extract information about the quality and intensity of motion. At the same time, real time feedbacks can be generated to stimulate the patient during an activity.

1.3.7 Virtual Reality

Virtual Reality (VR) technology involves users in environments that appear to be and feel similar to real-world objects and events, thanks to interactive simulations created with computer hardware and software. VR can be fully immersive or non-immersive, depending on the setup of the system. In case of fully immersive systems, the subject experiences a strong sense of presence, due to a realistic reproduction of the main stimulus (visual, auditory and tactile) that characterize the interaction with an environment. Non-immersive systems are simpler, usually composed by a monitor and an input device [44], [45].

(a) (b)

(c)

Figure 1.5 Motion controllers. (a) Kinect for Windows by Microsoft; (b) Nintendo Wii; (c) Nintendo wiiFit Balance Board.

All the techniques and devices described in the previous paragraphs, can be supported by and be part of VR systems. The principal role of VR in upper limb rehabilitation and in general in Neurorehabilitation, is to increase motivation and training effectiveness. VR permits the realization of goal-oriented and functional tasks for daily living [9], [34]. Furthermore, it offers the possibility to realize low cost rehabilitation systems that can be used at home and provide enhanced feedback about movement characteristics [46].

The combination of motion control systems and feedback generation permits to increase the amount of time dedicated to rehabilitation, without the assistance of a real therapist. Patients can practice motor activity at home being constantly monitored. Tele-rehabilitation and remote monitoring are adopted. Real time feedbacks will guide the patients executing functional exercises in a correct manner. The rehabilitation at home is no more supported just by the impression of the patient (self-reported measures) but, by the evidence of statics about the motion quality [45]. At the same time, the therapist will be updated about the quality and quantity of rehabilitation activity executed autonomously by the patient.

Obviously, VR systems are not dedicated just to home based rehabilitation, but are also useful supports for therapists. The advantage is the opportunity to design training protocols composed by functional activities, high number of repetitions and motivational feedbacks. In addition, all these properties can be supported by a high subject-oriented approach. Exercise and feedbacks can be selected by the therapist, in order to match the needs of a specific patient.

Starting from the positive premises of the VR in rehabilitation, researchers are largely testing how to adapt the gaming world to medical sciences. The words exergaming and serious games are actually used in rehabilitation and indicate games realized for specific type of patients, with the aim to execute rehabilitative exercises [45]. From gaming world, researchers are taking the experience in graphics and reproduction of feedbacks and motivational stimulus but, also technologies. Game controller as the Nintendo Wii [47] (Figure 1.5 (b)), the Nintendo WiiFit Balance Board [48] (Figure 1.5 (c)), and the Kinect sensor are used to permit the interaction with the VR and to track the motion of the patient. The adoption of games for general population is not optimal. These games can be too challenging for a patient and the tasks not oriented to the rehabilitation of the specific patient's issues [49].

Several studies demonstrate that the application of VR has benefits on UL rehabilitation but, his efficacy is not supported by generalizable results [45], [50]. The definition of the main features that the games for rehabilitation must have in order to be safe, feasible and effective, is still in progress. Therefore, the field of VR for rehabilitation is not completely explored, and, in conjunction with motor learning theory, offers material to take the cue from for the realization of interesting projects.

Chapter 2.

Kinematic model of upper limb and motion capture technologies

In the first chapter of this work, an overview of the existing technologies and methods adopted for the UL rehabilitation after stroke was presented. The potentiality of the VR in this field was highlighted. In fact, from the analysis of the state of the art of systems actually available and of clinical evidences on the application of several technologies and approaches, it is clear that interesting research activities can be conducted. The aim is to develop systems that must be low-cost, easy to set up, use and maintain, and that can be used also in a not clinical environment [49]. From the clinical point of view, VR is particularly suitable supporting the motor learning phenomenon. Thanks to VR, the rehabilitation protocol is presented as a game, or a set of games, and the patient will be induced to reach a goal, properly.

The ambition to develop such a kind of systems, must be supported by the right selection of the tools that will be integrated in the system. One or more sensors able to return information about the performances of the patient, and that permit the interaction with the VR, are necessary. Information about the motion of one or more parts of the body are required. So, motion tracking systems able to give data, in real-time and off-line, are tested in several studies and applications. The precision of the data returned by these devices is important, but a compromise between quality of the data and costs, dimensions, and usability of the device has to be accepted. In fact, clinical results suggest that the intensive training and the intervention at the early stage of the disease are important in order to have recovery of UL motility [18], [23], and this can be encouraged by systems that can be used autonomously by the patients, at home or at the hospital.

2.1 Upper limb description and kinematic models

Performing the rehabilitation of UL using VR and tools for automatic recognition of motion, requires a motion analysis. The motion of the segments of the UL has to be tracked and translated in data that can be used to analyze the quality of the motion and to reproduce that movement in a virtual environment. In order to perform a motion analysis, a kinematic model of the UL is necessary. To understand the output proposed by different motion tracking systems, it is necessary to talk about UL anatomy and about the simplifications on the kinematics model of UL.

2.1.1 Upper limb description and mobility

In this work only the skeletal subsystem of the UL will be considered. It can be isolated from soft tissues converting their relation with the bone as external actions and bones may be regarded as rigid bodies. The upper limb kinematics may then be analyzed and modeled in considering the skeletal components only [51].

For the proposal of this thesis, it is not necessary to include the hand in the UL model. So a model composed by five bones is considered. These five bones are the *clavicle*, the *scapula*, the *humerus*, the *ulna* and the *radius*, and form two mechanisms, the *shoulder* and the *elbow*. In Figure 2.1 (a) the bones are showed and in Figure 2.1 (b) and Figure 2.1 (c) the shoulder and elbow articulations are represented respectively.

Considering the connection between the bones, seven joints can be described, and are indicated in Figure 2.2 [51]:

- the *sterno-clavicular* (SC) joint, which articulates the clavicle by its proximal end onto the sternum;
- the *acromio-clavicular* (AC) joint, which articulates the scapula onto the distal end of the clavicle;
- the *scapulo-thoracic* (ST) joint, which allows the scapula to glide on the thorax;
- the *gleno-humeral* (GH) joint, which allows the humeral head to rotate in the glenoid fossa of the scapula;

- the *ulno-humeral* (UH) and *humero-radial* (HR) joints, which articulate both ulna and radius on the distal end of the humerus;
- the *ulno-radial* (UR) joint, where both distal ends of ulna and radius join together.

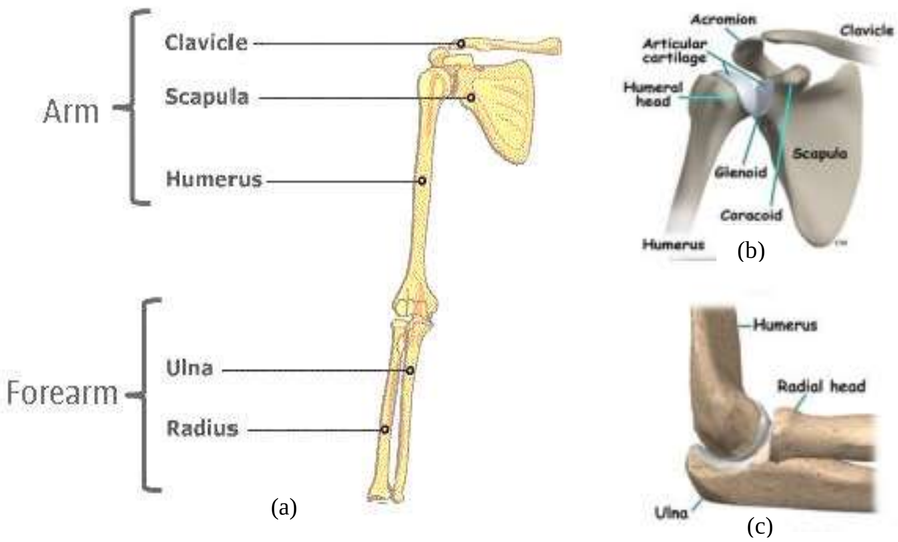
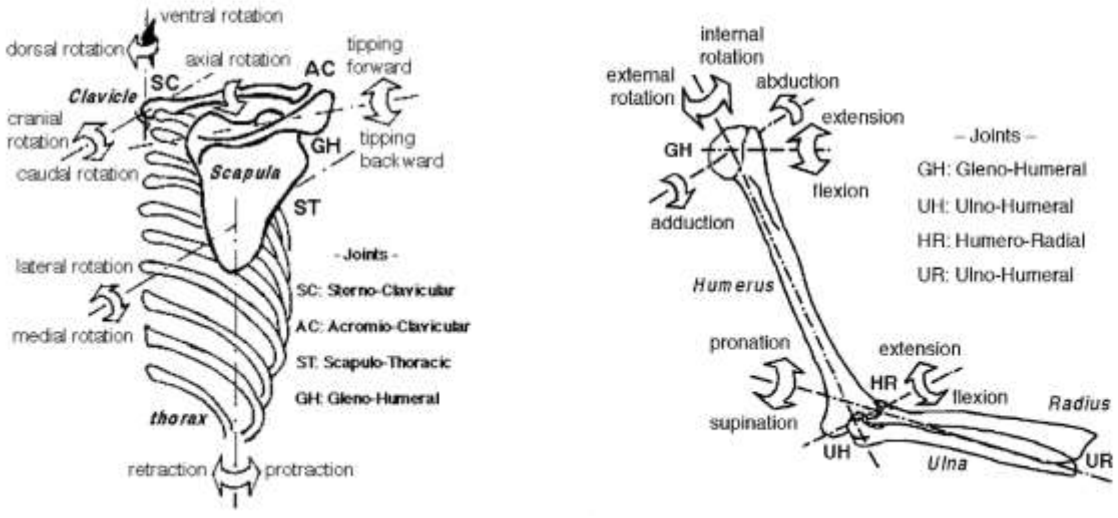


Figure 2.1 Bones of the Upper Limb. (a) The upper limb is composed by: clavicle, scapula, humerus, ulna and radius; (b) Shoulder articulation; (c) Elbow articulation.

Each of these joints, except the ST joint, can be assumed to allow 3 degrees of freedom (DoF) in rotation, and has a specific role in upper limb motion. It is clear that the shoulder is a complex system and a series of simplifications are usually applied to the UL model. Translations can be overlooked, the scapula is assumed constrained to the thorax and the scapula and clavicle can be excluded, describing only the movement of the humerus relative to the thorax [52].

The resulting upper limb movements are showed in Figure 2.2 and summarized in Table 2.1 Because the small range of motion associated to the pronation/supination of the forearm (5°, as wrote in Table 2.1), this rotation can be neglected too. A representation of each motion is showed in Figure 2.3.

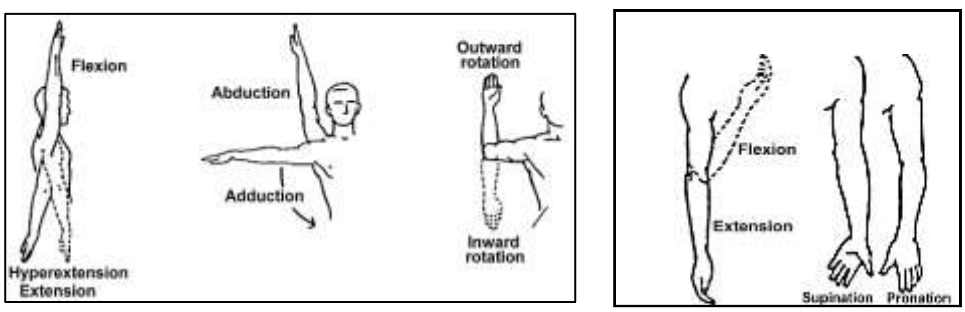


(a) (b)

Figure 2.2 The upper limb movements. (a) Shoulder movements; (b) arm and forearm movements [51].

Table 2.1 Upper limb movements. The motions that interest each part of the upper limb are summarized ad the joints that control the motions are specified. The scapula-thoracic motion and the motions associated to the wrist and the hand are not considered.

Region	Joint	Motion
Forearm	Ulno-radial (UR)	5 degrees of supination/pronation
Elbow	Ulno-humeral (UH) Humero-radial (HR)	Flexion/Extension
Shoulder	Gleno-humeral (GH)	adduction/abduction, outward/inward rotation, flexion/extension
	Acromio-clavicular (AC)	90 degrees of adduction/abduction
	Sterno-clavicular (SC)	maximal elevation

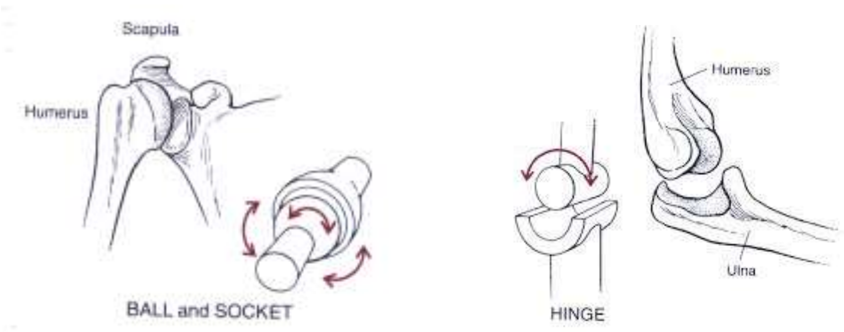


(a) **(b)**

Figure 2.3 Representation of (a) shoulder motions and (b) elbow motions.

2.1.2 Kinematic model of upper limb

The description of UL anatomy and mobility in the previous paragraph, suggests that 4 DoFs can be used to describe the motion of the UL, if wrist and hand are neglected. The shoulder can be modeled as a ball and socket joint (Figure 2.4 (a)), with his 3 DoFs for flexion/extension, adduction/abduction and internal/external rotation, and the elbow as a hinge joint (Figure 2.4 (b)), with 1 DoF for flexion/extension.



(a) **(b)**

Figure 2.4 Representation of (a) the shoulder articulation as a Ball and Socket joint and (b) of the elbow articulation as a Hinge joint.

The International Society of Biomechanics (ISB) proposes a definition of a joint coordinate system for the components of human body [53], and the coordinate systems suggested for humerus, and forearm are showed in Figure 2.5. Rotations are described using Euler angles decompositions of relative orientation of the distal segment relative to a proximal segment. The ISB suggests how to locate the coordinate systems using specific anatomical landmarks, that can be a reference for the researcher that use markers or other kind of sensors to determine the bones rotation. In Figure 2.5 the rotation order specified by the ISB are showed. For the humerus, Figure 2.5 (a), the order was chosen as rotations about the y-x'-y'' axes. The flexion/extension and pronation/supination angles for the forearm were considered independent [53]. The coordinate systems and the Euler angles suggested by the ISB are not a mandatory, and different models are adopted by scientists [52].

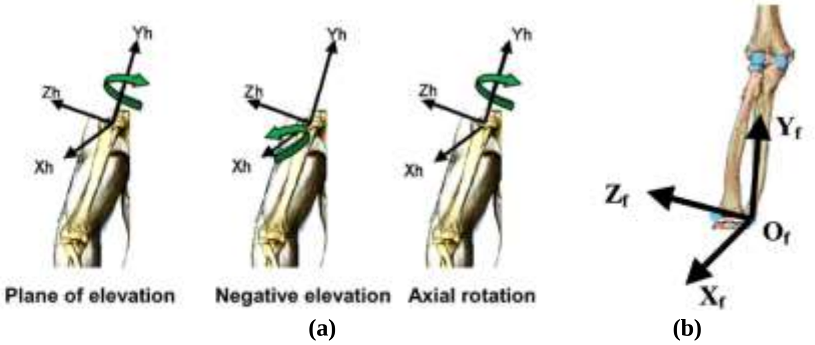


Figure 2.5 Definition of local coordinate systems of (a) humerus and (b) forearm [53].

2.2 Motion tracking systems adopted in upper limb rehabilitation

There are several approaches to the UL motion analysis, that differ in the kinematic model or the motion tracking technology adopted. A human motion tracking system is composed by motion sensors that must generate real-time data that dynamically represent the pose changes of a human body. Zhou and Hu, 2008 [54] review the main motion tracking technologies for rehabilitation, offering a comparison between the different sensor technologies that can be used (Table 2.2). These technologies are reported in the diagram in Figure 2.6 and are divided in three principal groups: non-visual tracking, visual tracking and robot-aided tracking systems.

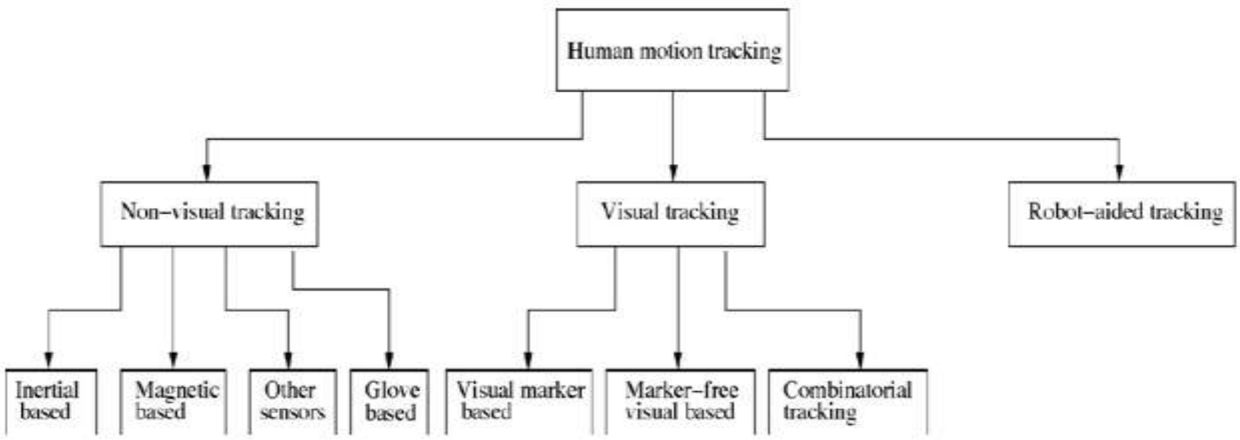


Figure 2.6 Classification of human motion tracking using sensor technologies [54].

Table 2.2 Performance comparison of different motion tracking systems proposed by *Zhou and Hu*, 2008 [54].

Systems	Accuracy	Compactness	Computation	Cost	Drawbacks
Inertial	High	High	Efficient	Low	Drifts
Magnetic	Medium	High	Efficient	Low	Ferromagnetic materials
Ultrasound	Medium	Low	Efficient	Low	Occlusion
Glove	High	High	Efficient	Medium	Partial posture
Marker	High	Low	Inefficient	Medium	Occlusion
Marker-free	High	High	Inefficient	Low	Occlusion
Combinatorial	High	Low	Inefficient	High	Multidisciplinary
Robot	High	Low	Inefficient	High	Limited motion

2.2.1 Non visual-tracking systems

In the non-visual-tracking systems are included the inertial, magnetic and ultrasound based systems and the gloves. These technologies are usually low-cost, as reported in Table 2.2. The sensors are placed on the human body in order to collect movement information. Each technology has advantages and limitations, and can be appropriate to specific environments and applications [52], [54].

In the inertial sensor group, the accelerometers and the gyroscopes can be mentioned. An accelerometer is a compact and lightweight sensor that convert linear and/or angular acceleration into an output signal. A gyroscope measures rotation velocity with regards to a single axis. As specified in Table 2.2, inertial sensors suffer from the “drift problem” if they are used to estimate velocity or orientation. On the other hand, they present a high sensitivity and covers large capture areas, do not need any complimentary emitter/sensor to work, so their accuracy does not depend from other sensors and does not change if the subject moves in the environment. Furthermore, no occlusion issues affect the inertial sensors. A popular example of inertial system, used primarily in gaming, is the Nintendo Wii™ Controller [55], used also in rehabilitation [47]. Generally, the subject hold two trackers, so the motion of the hands is tracked [47], but the inertial sensors can be placed on different parts of the body in order to control specific motions [56].

Magnetic-based technologies are used in virtual reality applications. They are composed by one or more magnetic field emitter and a certain number of trackers, devices that measure the quasi-static direct current fields or a changing magnetic field produced by the active source [57]. Size, high sampling rate and the lack of occlusion are the main features of this type of motion tracking solutions, but latency and jitter reduce the usability of these systems. An example is the STEM System, produced by SIXENSE [58], a wireless motion tracking system that support up to five motion tracker for the tracking of parts of the body (hands, head or other parts). It is worth to notice that this kind of systems are sensitive to the position of the magnetic field emitter, so the accuracy will depend on the location of the tracker with respect to the emitter. Furthermore, ferromagnetic and conductive materials can affect the magnetic field shape [54], [57].

In the “other sensors” group, cited in Figure 2.6, can be included acoustic systems, ultrasonic systems and devices that monitor bio-signals related to motion, as the electromyogram (EMG), that is an analysis of the electrical activity of contracting muscles [59].

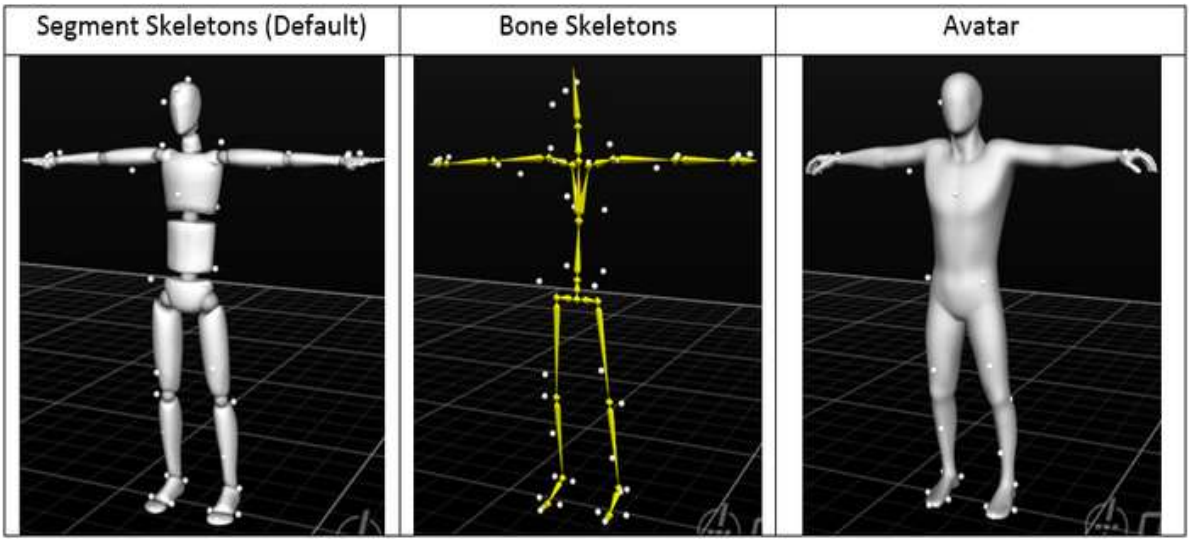
Finally, the gloves are complex systems that are used to track the motion of the hand, and are largely used in case of hand impairment [60].

2.2.2 Marker-based visual-tracking systems

A visual-tracking system is composed by: light sources and optical sensors. In the marker-based visual-tracking systems, the light sources are identifiers applied on the body of the subject, in specific positions. These identifiers, the markers of the tracking system, can be passive (materials that reflect the ambient light), or active (emitter of internally generated light) [54], [57]. At least two optical sensors are used to calculate the markers position in the 3D space. Specific softwares are used to estimate the body pose, following specific steps. These steps are followed by all the existing marker-based visual-tracking systems, as VICON [61], CODA [62] or Polaris [63].

Another system is the OptiTrack [64] created by NaturalPoint, available at the University of Calabria – Department of Mechanical, Energy and Management Engineering, and used for the development of part of this thesis. In Figure 2.7 the steps of the body tracking system are summarized, using frames captured from the optical motion tracking software associated to OptiTrack, called Motive [65]. First of all, the markers should be placed on the body of the subject that will be tracked. These markers must be placed on the respective anatomical location of the skeleton (Figure 2.7 (a)), that are pre-programmed. The markers can be placed on a suit, Figure 2.7 (b) or onto the skin, Figure 2.7 (c). When the markers placement is completed, the skeletons can be created in the virtual environment. The subject is asked to stay in a calibration pose, that often correspond to the T-pose, showed in Figure 2.7 (a) and (b). The software will recognize the markers associated to the anatomical joints and create the skeleton model, that can be visualized as a segment skeleton (Figure 2.7 (d)), a bone skeleton (Figure 2.7 (e)) or an avatar (Figure 2.7 (f)). The transformation matrix of each anatomical joint are then captured and are available for analysis.

(a) **(b)** **(c)**



(d) **(e)** **(f)**

Figure 2.7 Steps to prepare the optical motion tracking software. The Motive software is considered. (a) Marker placement model; (b) Subject wearing a suit where the markers are arranged as in the model; (c) Placement of the markers onto the skin; (d) Skeleton displayed in the software interface as a segment skeleton; (e) Skeleton displayed in the software interface as a bone skeleton; (f) Skeleton displayed in the software interface as an avatar. [66]

The marker based systems present the occlusion problem, that limits the accuracy of the tracking when the subject executes complex movements. Furthermore, this kind of systems limits the space of execution of the motion, that corresponds to the space visible to the cameras. Finally, the application of markers on the skin or on a suit introduces errors due to the soft tissues [54].

2.2.3 Marker-less visual-tracking systems

Marker-less visual-tracking systems can resolve several problems of marker-based systems. In fact, these systems are inexpensive and do not require the application of markers on the body of the subjects, avoiding the errors due to the motion of soft tissues or to the occlusion of the markers [54], [67].

The identification of the body joints starts from the silhouette of the subject. The first step is the subtraction of the background, in order to obtain only the shape of the body. Then, different algorithms can be adopted in order to obtain the segmentation of the body, that can use an explicit shape model (model based systems) of the body, or not (model free systems), and to estimate the body pose [68].

There are several commercially available products, as the Organic Motion's marker-less motion capture technology [69] or Simi Shape [70], but the most popular is the Kinect sensor, the depth camera produced by Microsoft [5].

2.2.4 Kinect for Windows sensor: how does it work?

The Kinect sensor is a low cost device, that can be used for entertainment, fitness, rehabilitation. It is easy to use and offers a wide range of applications, that can be related to the human body tracking or to the object tracking. It has been introduced on the market in 2010 with the first version (Kinect v1.0). In 2014 a new version, the Kinect v2.0, has been released.

The Kinect v2.0 is composed by a color camera, an IR (infrared) camera, an IR projector and a microphone array (Figure 2.8). In Table 2.3 the main features of the Kinect sensor are summarized. The two versions of the sensor (v1.0 and v2.0) are compared. Developers and

researchers can use the sensor thanks to the official Microsoft SDK [71], that provides the drivers and a set of functions and code samples for own implementations.
The Kinect v2.0 uses the time-of-flight principle: the distance to be measured is proportional to the time needed by the active illumination source to travel from emitter (IR projector) to target [72], [73].

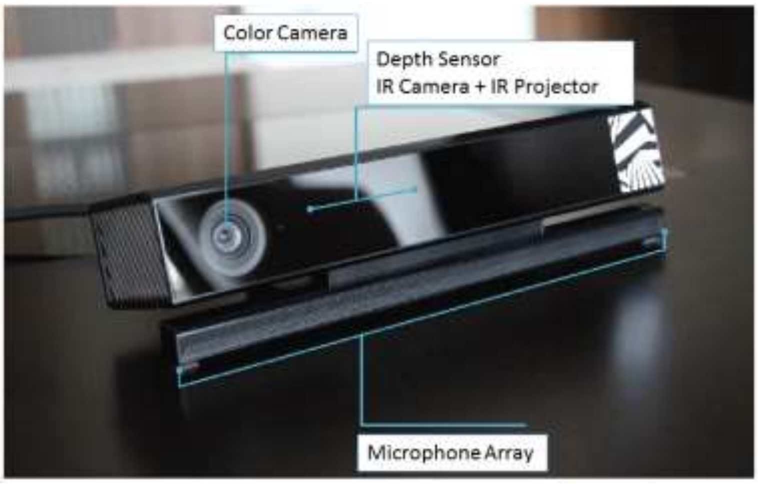


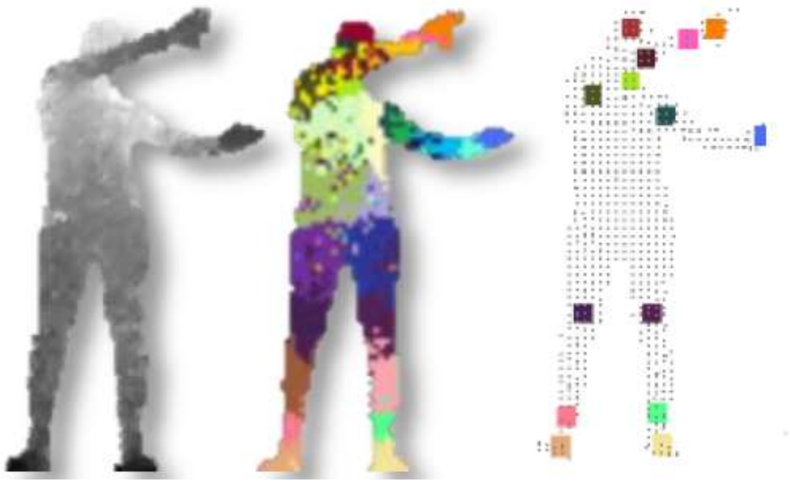
Figure 2.8 Kinect v2.0 sensor. It is composed by a color camera, a depth sensor and a microphone array.

Table 2.3 Comparison between Kinect for Windows v1.0 and Kinect for Windows v2.0.

Feature	Kinect for Windows 1	Kinect for Windows 2
Color Camera	640x480 @ 30 fps	1920x1080 @ 30 fps
Depth Camera	320x240	512x424
Max Depth Distance	~4.5 m	~ 4.5 m
Max Depth Distance	40 cm	50 cm
Horizontal field of view	57 degrees	70 degrees
Vertical field of view	43 degrees	60 degrees
Skeleton Joints Defined	20 joints	25 joints
Full Skeletons Tracked	2	6

The Kinect uses the Continuous Wave Intensity Modulation approach. The scene is actively illuminated using near infrared intensity-modulated, periodic light. Due to the distance between the camera and the object, and the finite speed of light *c*, a time shift Φ [s] is caused in the optical signal. This shift is detected in each sensor pixel by a so-called mixing process. The time shift can be easily transformed into the sensor-object distance as the light has to travel the distance twice, i.e. $d = \frac{c\emptyset}{4\pi}$ [73].

Using the Time of Flight (ToF) approach, the distance between each object in the scene and the sensor is computed and represents the depth image used by the motion tracking algorithm. In order to predict 3D positions of body joints from a single depth image, using no temporal information, an object recognition approach was adopted [74].
A large database of motion capture of human actions has been recorded and used to train a model able to classify semi-local body part in a wide variety of poses. The input of the software is the depth map containing only the shape of the subjects in the scene (Figure 2.9 (a)). On this image a probabilistic labeling is executed and each pixel is labeled as appertaining to a specific part (Figure 2.9 (b)). This classification is done considering the depth of the pixels. Each part contains an anatomical joint of interest, and their 3D coordinates are computed thanks to the application of a mean shift algorithm, that compute the center of mass of a dense distribution of points (body part in the depth image) (Figure 2.9 (c)) [74].
As reported in Table 2.3, the Kinect for Windows v2.0 allows the identification of 25 joints. These joints are showed in Figure 2.10, where the skeleton positions returned by the Kinect, are associated to anatomical joints.



(a) (b) (c)

Figure 2.9 Workflow of the body pose estimation algorithm adopted by the Kinect. (a) Depth map of the body shape; (b) Body parts identified by different colors; (c) Joints position identified in the body parts [74].

Figure 2.10 Skeleton positions relative to the human body.

The accuracy of the Kinect v2.0 has been estimated to be at the centimeter level [43]. The error sources can be different [72], [73]:

- Ambient background light: it can lead to over-saturation in case of too long exposure times;
- Multi-device interference: using more than one Kinect contemporary can lead to interferences, i.e. the active illumination of one camera influences the result of another camera;
- Temperature drift: the computed distance values change during the devices warm-up;
- Systematic distance error;
- Depth inhomogeneity: light reflected by different depths can cause the effect of mixed pixels, that lead to wrong distance values;
- Multi-path effects: the active light may not only travel the direct path from the illumination unit via the object surfaces to the detector;
- Semitransparent and scattering media: media that does not perfectly reflect the incident light potentially causes errors;
- Dynamic scenery: motion may alter the true depth.

The Kinect sensor has then the pro to be low cost, easy to use and able to track 25 joints without the application of markers. The accuracy of this tool is not comparable with the accuracy of marker-based systems, that can be in the order of millimeters, but it is largely tested in several applications for rehabilitation, as discussed in Chapter 1, and promising results are emerging.

Chapter 3.

A preliminary Analysis on Performance Evaluation of Kinect v2 for Upper Limb Rehabilitation Applications

Modern upper limb rehabilitation systems use motion tracking technologies to evaluate patient performance, to aid limb motion in robotic assisted rehabilitation techniques or to allow interaction with virtual reality [54]. Shoulder, elbow and wrist joints tracking, is a necessary step for motion classification and recognition [75]. Furthermore, upper limb tracking allows to develop patient-specific therapies and is used to create serious games that induce motor recovery in a stimulating environment [76]. Assisted motion control is also fundamental for the application of autonomous or semi-autonomous systems for motor recovery and to make rehabilitative experience possible at home [9].

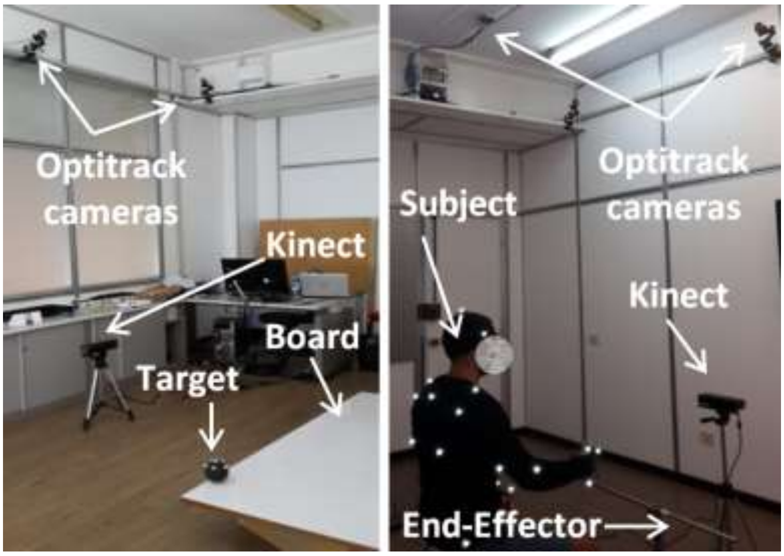
Several studies have compared the Kinect with marker-based systems in terms of body tracking precision. Kinect performance was studied using three main approaches: posture detection [77] [78] [79], joints center evaluation [80] and angles evaluation [81]. In particular, Xu & McGorry [80] very recently proposed a comparison between the first and second generation of the Kinect and a marker-based system, concluding that no impressive improvements are introduced by the new version of the Kinect if the tracking is assessed at the whole skeleton level for static posture evaluation. It is to be noted, however, that most of the available studies consider only the first generation of the Kinect [81] [77] [78], so the advantages of the second generation are not completely addressed, especially in the upper limb rehabilitation field.

The aim of this part of the study is thus to validate the reliability of the second generation of the Kinect when adopted for upper limb rehabilitation. The work was conducted by taking into consideration (i) the possibility to use the sensor in different positions without calibration, (ii) the body tracking algorithm, already integrated in the Kinect software, and (iii) the availability of depth images to track specific objects. A marker-based system was also used to conduct a two-step complementary evaluation. Initially an object detection test was performed to generally assess the device performance. In particular, a spherical target was identified from the depth images captured by the Kinect and from the marker-based system data as well. This step was useful for a first comparison between the two systems in terms of precision. At the same time, it allowed to investigate the potentiality of the new version of the Kinect to detect objects during rehabilitation sessions. Indeed, object detection and tracking can be integrated in the rehabilitation process, to give more realistic stimuli to the patient [82]. The second step of the study dealt with the evaluation of the upper limb tracking performance. Right shoulder, elbow and wrist joint positions were captured with both marker-based and marker-less systems and the shoulder and elbow angles were computed and compared, during specific upper limb motions. An evaluation of the trajectories of the wrist was also performed. In order to assess the effect of the relative location between the Kinect sensor and the observed subject, the sensor was placed in several different positions and orientations and results were compared. The upper limb motion was executed by a healthy subject guided by the use of a specific end-effector as to emulate the movements usually asked to the patient during a robot-assisted rehabilitative session, e.g. the “reaching” and the “side to side” exercise [83] [84] [85]. In fact, whereas in other studies [80] [81] the participants were asked to execute standard motions such as shoulder abduction-adduction or shoulder flexion-extension, in this study the performances of the Kinect are compared to that of a marker-based system, for specific complex movements, affecting both the shoulder and elbow rotation simultaneously.

3.1 Materials and methods

Object and upper limb tracking were performed using the second version of the Microsoft Kinect for Windows and a stereo-photogrammetric optical system, the Optitrack [64], consisting of 8 Flex13 cameras acquiring up to a frequency of 120 Fps. For object detection, a spherical target was considered, only depth frames were captured by the Kinect, and the Matlab Image processing toolbox (The MathWorks, Inc.: Image Processing Toolbox –

MATLAB, 2015) was used to retrieve position data. For body tracking, the Kinect body model and joints position were obtained from the associated Software Development Kit (SDK) v2.0 [5], working at up to 30 Fps. For the Optitrack system, the NatNet SDK v2.7 [64] was used to determine the positions of the reflective markers attached on the surface of the spherical target and the Motive 1.7.5 software [64] was adopted to capture the body joints position in conjunction with a motion capture suit and reflective markers. Figure 3.1 shows a photograph of the experimental setup used in this present work. In particular, Figure 3.1(a) shows the setup used for object detection and Figure 3.1(b) shows the one for the upper limb tracking. In the figures both the Kinect sensor and the Optitrack cameras are indicated, as well as the corresponding coordinate systems used to retrieve numerical values.



(a) **(b)**

Figure 3.1: Experimental setup for (a) object detection and (b) upper limb tracking.

3.1.1 Object Detection

The object detection was conducted by placing a spherical target on the six holes of a 1750 mm x 900 mm board, as shown in the detail of Figure 3.2. The holes are drilled by a numeric control milling machine with a precision of a few order of magnitude higher than that of the Optitrack systems, used for reference. The relative position of each hole was thus known with confidence. The target consisted of a black plastic sphere with a radius of 45 mm. A pin was attached on the back of the sphere to guarantee its correct placement onto the board holes: indeed, the centre of the sphere was aligned to the centre of the holes. In order to detect the target with the Optitrack system, six reflective markers were placed on the upper surface of the spherical target, as detailed in Figure 3.2.

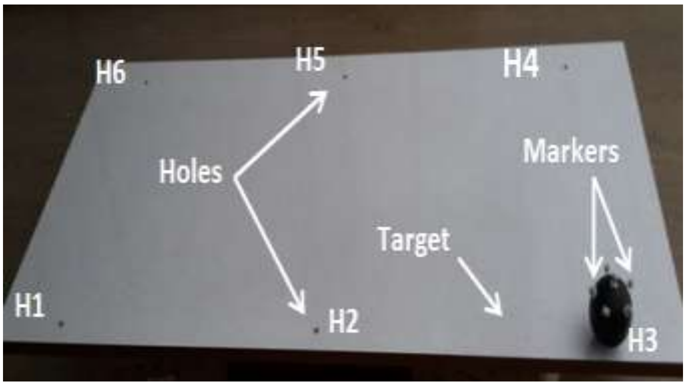


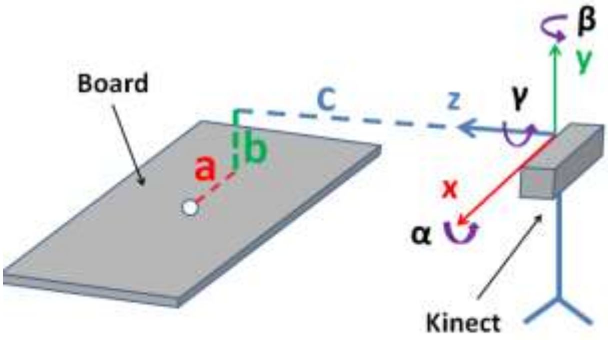
Figure 3.2 Board with the six holes and target used for object detection. The target is a black plastic sphere, on the surface of which six reflective markers are applied for detection using the Optitrack system. Holes are labelled from H1 to H6 for reference.

Table 3.1 Definition of the five board positions, relative to the Kinect, as represented in Figure 3.3(b). α, β and γ are the rotations around the x, y and z axis, respectively.

Board Pose	a [mm]	b [mm]	c [mm]	α [deg]	β [deg]	γ [deg]
B1	0	-150	2000	~0	~0	~0
B2	0	-150	2000	~10	~0	~0
B3	0	-150	2000	~0	~0	~20
B4	0	300	2000	~90	~0	~0
B5	0	300	2000	~80	~0	~0

The board was placed on five different combinations of positions and orientations, as detailed in Figure 3.3 and Table 3.1, and for each of them, the target was placed in all of the six holes of the board. Measured data from the two systems were synchronized and, for each target position, 50 frames were considered for data analysis.

(a)



(b)

Figure 3.3 Board position relative to the Kinect. (a) Photo of the board in position B1, as defined in Table 1; (b) Schematic representation with parameters used in Table 3.1.

For the Optitrack system, the NatNet SDK was used to identify the center of the reflective markers placed on the surface of the target. The Cartesian coordinates of these centers were used to fit a sphere and then to compute the position of the target center in the Optitrack coordinates system. The standard deviation (STD) of the spherical target center coordinates for the 50 frames was used as an indication of the precision of the Optitrack system, in terms of robustness to noise, environmental effects (e.g. ambient lightening), resolution of the optical components. In particular, the three values for the STD, corresponding to the three X-Y-Z coordinates, of the six target center were estimated for each of the five different positions of the board and reported in Section 3 below.

For the Kinect system, depth frames were captured and Matlab Image Processing Toolbox (The MathWorks 1994-2015) was used for image processing, data filtering and shape detection in order to identify the position of the target. In particular, each depth image was transformed into a binary image by a thresholding [86], in order to filter the pixels with a depth value greater than an optimal value. The binary image was then segmented using a watershed transformation algorithm [87] and the target was filtered by size and eccentricity parameters. The intrinsic parameters of the Kinect depth sensor (focal length and principal point coordinates), returned by a specific method of the Kinect SDK, were used to transform the pixel coordinates in the Cartesian coordinates of the Kinect coordinate system. The STD of the X-Y-Z coordinates of the target center for the 50 frames were calculated and used as described above for the Optitrack analysis, to assess the precision performance of the Kinect as well.

To estimate the accuracy of the two optical systems in computing the exact position of the target on the board, a subsequent analysis is performed. A geometric plane (modelling the reference board) with six specific points (modelling the reference holes) is fitted to the six measured locations for the target center, for each board pose. The root-mean-squared-deviations (RMSDs) of the residual errors of such fitting procedure are used to assess the performance of the detection process, in terms of accuracy rather than precision. Results are reported in Section 3 below.

This particular strategy, adopted to assess the accuracy, allowed to cope with the issue related to the different absolute coordinate systems of the Kinect and Optitrack devices and thus to effectively compare results of both optical systems.

Table 3.2 Definition of the six Kinect position used for upper limb tracking.

Position	**a [mm]**	**b[mm]**	**c [mm]**
K1 – right down	800	800	-2000
K2 – right up	800	1500	-2000
K3 – middle down	0	800	-2000
K4 – middle up	0	1500	-2000
K5 – left down	-800	800	-2000
K6 – left up	-800	1500	-2000

3.1.2 Upper limb tracking

During the second step of the study presented in this work, it was asked an healthy subject to make a set of movements using a passive end-effector. In particular, the end-effector which was visible in Figure 3.1(b) and is now shown in the detail of Figure 3.4, consisted of a tripod and a bar fixed on it. It was made to constrain the hand movement of the subject to a circular or linear motion, so that a reference trajectory was available for validation. Each session was recorded by using both the Kinect and the Optitrack system.

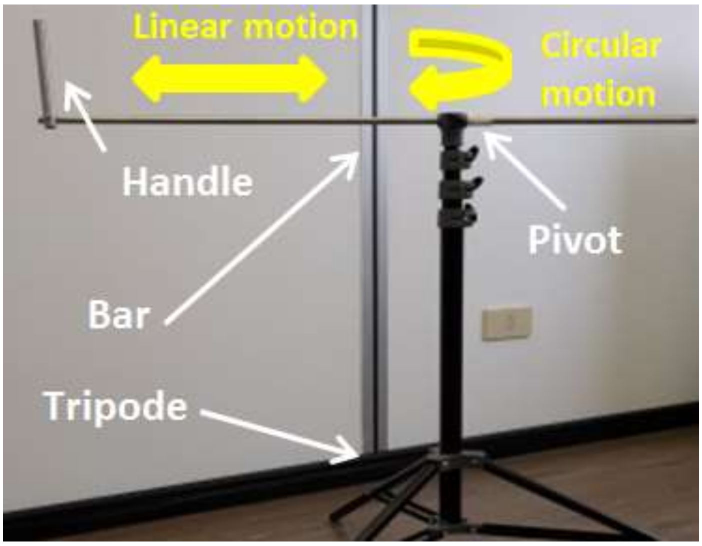
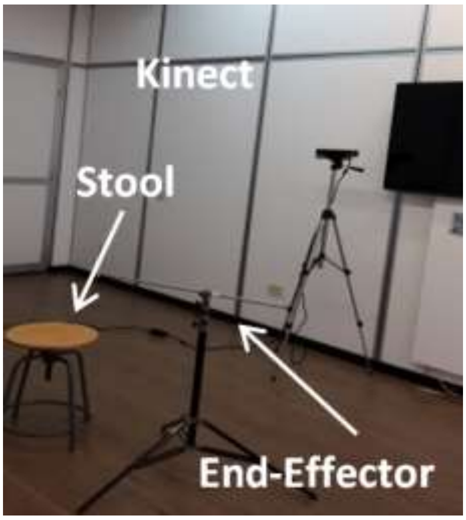
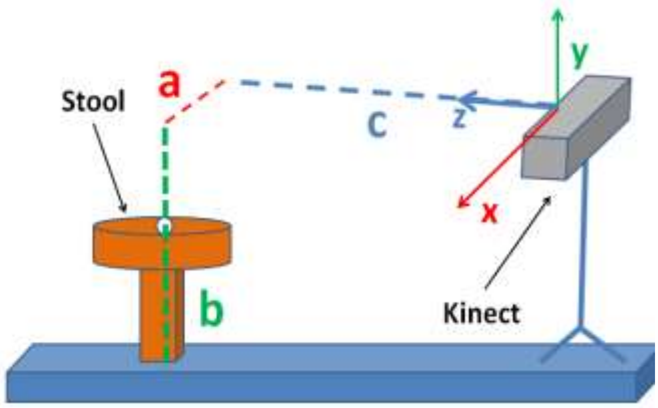


Figure 3.4 End-effector used for upper limb motion. It consists of a tripod and a bar. On the extreme of the bar there is an handle, used to facilitate the prescribed linear and circular motion.

The healthy subject was seated on a stool, placed in the field of view of the Optitrack cameras and the Kinect was placed in six different positions as illustrated in Figure 3.5, but oriented so as it was facing the stool. The different positions where the Kinect was located are defined to be at the right, middle and left position relative to the axis orthogonal to the subject front plane, as defined in Table 3.2. For each of these positions, the Kinect was located at two different distances from the floor, respectively at about 800 mm and 1500 mm. In Table 3.2 these positions are summarized and labeled from K1 to K6 for ease of reference. The subject was wearing a motion capture suit with reflective markers to identify the shoulder, elbow and wrist joint, as shown in Figure 3.1(b). Such analysis is performed to investigate if the Kinect position relative to the subject was somehow affecting the overall tracking procedure. A circular motion and a linear motion were thus executed by the right hand of the healthy subject for each position of the Kinect, as described above. It is worth noting that the healthy subject was asked not to rotate the wrist during the constrained motion, even if some small effect due to this compliant requirement are expected to affect the obtained results reported in Section 3. The Kinect and the Optitrack frames were synchronized using the timestamp for direct comparison.

To determine the shoulder and elbow angles from the coordinates of the position of the shoulder, elbow and wrist joints obtained from the two optical systems, a 4 degree-of-freedom (DOF) inverse kinematic model of the human arm was used [88]. A schematic model of the upper limb with geometric parameters and joints variable is represented in Figure 3.6. The shoulder is modeled as a ball-and-socket joint with rotation axis for abduction-adduction (angle q_1), flexion-extension (angle q_2) and internal-external rotation (angle q_3).





(a) (b)

Figure 3.5 Kinect position relative to the subject for upper limb tracking. Parameters are given in Table 2. (a) Photograph and (b) Schematic representation

For the elbow joint, only the functional flexion-extension axis (angle q_4) is considered. The expressions for the solutions of the inverse kinematics model are reported below as

$$q_1 = \arctan\frac{-{}^{(1)}y_3}{{}^{(2)}y_3}, \qquad (1a)$$

$$q_2 = \arcsin {}^{(3)}y_3 \ , \qquad (1b)$$

$$q_3 = \arctan \frac{{}^{(3)}z_3}{{}^{(3)}x_3}, \qquad (1c)$$

$$q_4 = \arcsin \frac{l_u^2 + l_f^2 - \|\boldsymbol{w} - \boldsymbol{s}\|^2}{2 l_u l_f}, \qquad (1d)$$

where arctan is the four quadrant inverse tangent function, and, with reference to Figure 3.6, $\boldsymbol{x}_3$, $\boldsymbol{y}_3$ and $\boldsymbol{z}_3$ are the unit vectors of the reference axes on the elbow joint, l_u and l_f are, respectively, the arm and forearm lengths, and $\boldsymbol{s}$ and $\boldsymbol{w}$ the shoulder and the wrist position vector, respectively.

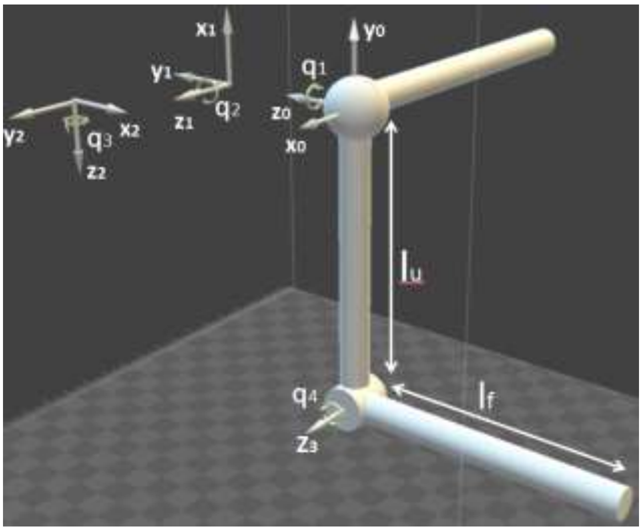


Figure 3.6 Schematic model of the upper limb with geometric parameters and joints variable, as defined in [88].

It is worth noting that, the inverse kinematic model reported in [88] assumes that the human subject is not moving the trunk, so that the position of the shoulder is considered to be fixed. The RMSDs between Optitrack angles variation and Kinect angles variation were computed, to give an indication of the difference between the two systems.

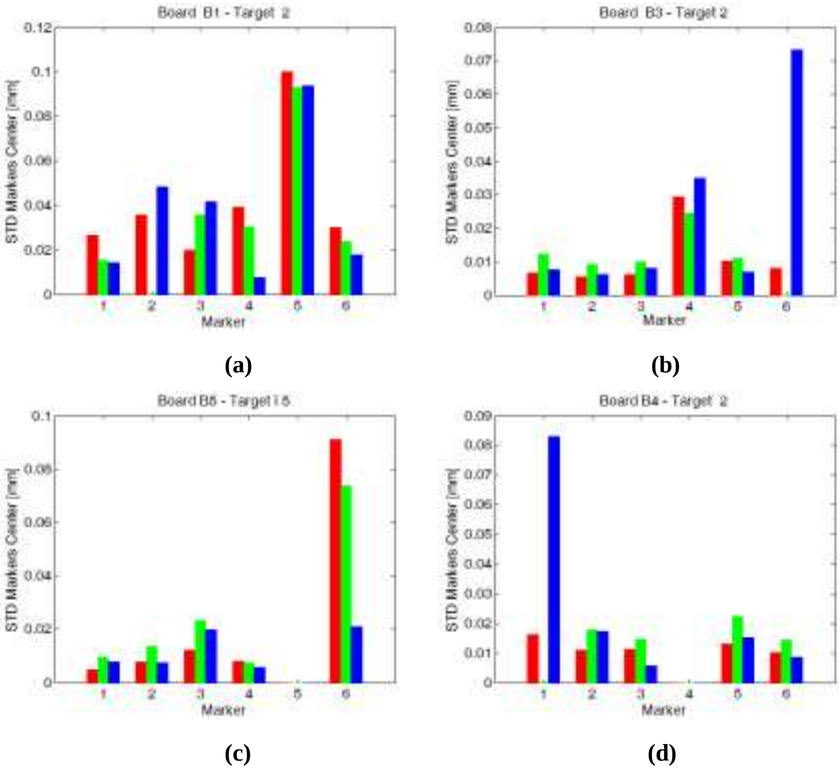
The trajectory described by the wrist as computed from the two optical system for each session, is also used to assess the performance of the two motion tracking systems. In particular, a best-fit plane was determined on the set of points corresponding to the wrist position during motion. This is because the motion constrained by the end-effector was planar and this allowed to preliminary filter the results. Once projected on the corresponding best-fit plane, a second fitting was performed on the projected trajectories to fit a circle and a line, respectively, for the circular motion and for the linear motion of the hand grasping the end-effector. The RMSD of the residual errors of each fitting procedure, the radius of the fitted circle and the range of motion (RoM) for each trajectory were computed.

3.2 Results

To preliminary assess the precision at source of the Optitrack system used for reference, the coordinates of the position of the six reflective markers placed on each of the target location and for each of the board pose were considered. In particular, for each board position and for each target location, the STD of the three X-Y-Z coordinates of the six reflective markers position for the whole set of 50 acquired frames are computed, and results are reported in Figure 3.7 for the four most critical cases. This helped in obtaining a qualitative indication of the performance of the Optitrack system at source, i.e. in directly identifying the reflective markers without any filtering or post-processing technique. It can be seen from Figure 3.7 that the general trend of the STD confirms the relative high precision of the system. However, it is possible to observe some reflective marker with a higher deviation, for example markers of target in position 2 for the board orientations B1, B3 and B4. This result was dependent on the camera settings, and in particular on the sensitivity to the infrared light reflected by the marker. Also the observability of the reflective marker by some of the cameras was a critical issue.

In Figure 3.7(c) and (d) there is a marker where no value is reported, respectively marker 5 in Figure 3.7(c) and marker 4 in Figure 3.7(d). These markers were not observable by the Optitrack system. Indeed, in those configurations, the board was in a vertical position and the aforementioned markers were on the spherical surface facing the floor.

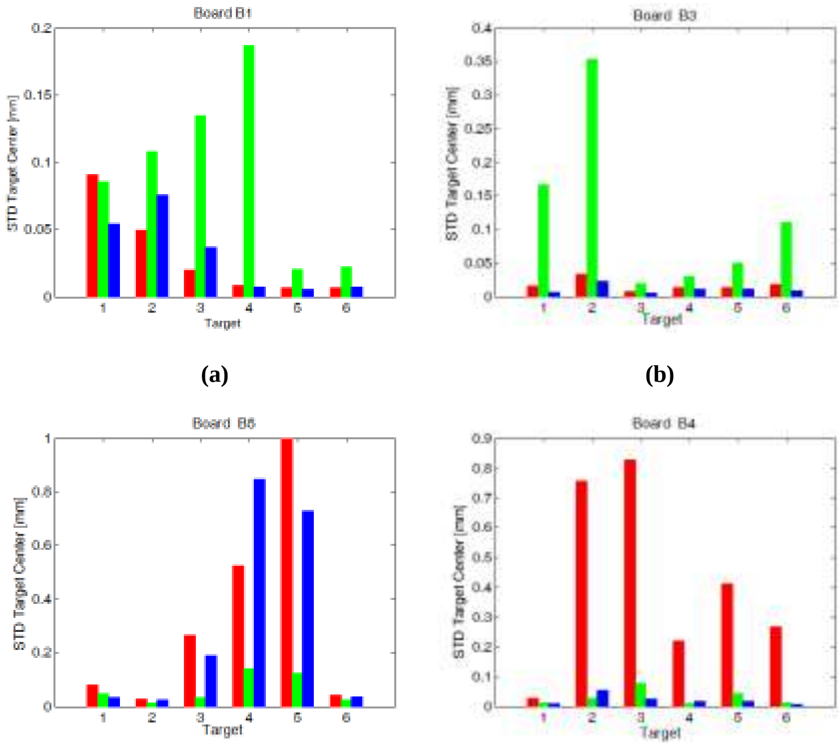
In Figure 8 the STDs of the spherical target center coordinates for the same four board positions of Figure 3.7 are illustrated and, because of the previous observation on Figure 3.7(c) and Figure 3.7(d), the STD on the coordinates of the spherical target center for board pose B4 and board pose B5, showed in Figure 3.8(c) and Figure 3.8(d) respectively, are higher than the other configurations. As a representative single-value estimate of the Optitrack precision, the average value of the radii of all the fitted spheres and the corresponding standard deviation were considered. It resulted that the mean value was 52 mm and the deviation was 1.4 mm, thus suggesting an error of about 1 mm on the target position detection by the Optitrack system. It is noted that the identified average radius resulted from the radius of the spherical target (45 mm), plus the radius of the reflective marker (5 mm), plus an uncertain thickness of a few millimeters for the material used to attach the reflective markers to the target.



(a) (b)

(c) (d)

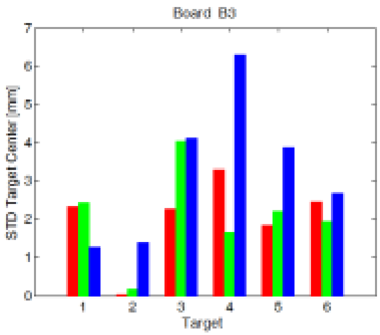
Figure 3.7 Estimate of the Optitrack resolution at source for the four worst cases. RMSD of the coordinates of the six reflective markers for specified target and board pose, as indicated. With reference to the coordinate system in Figure 3.3, red bars indicate the x coordinate, green bars the y coordinate and blue bars the z coordinate.



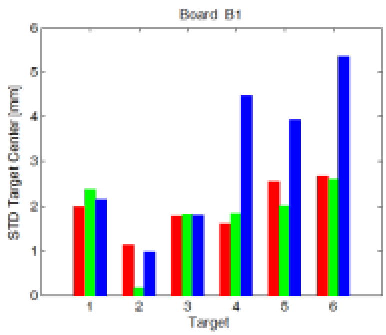
(a) (b) (c) (d)

Figure 3.8 Estimated precision of the Optitrack system for the four worst board positions. STD of the spherical target position. With reference to the coordinate system in Figure 3.3, red bars indicate the x coordinate, green bars the y coordinates and the blue bars the z coordinate.

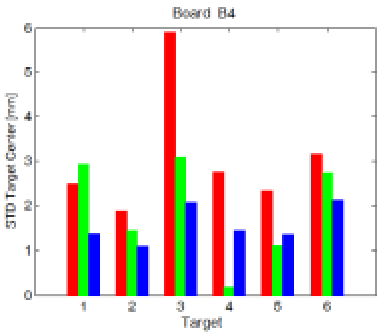
For the Kinect, the tracking procedure was also influenced by the target position in the field of view of the device. In Figure 3.9 the STD of the coordinates of the spherical target center at the six positions on the board, for the four board orientations, captured by the Kinect are illustrated. In Figure 3.9(a)-(d) for the target position 2, it is possible to observe a lower STD because that position was on the middle of the depth frame for all of the board orientations. The highest STD was obtained for board pose B3 (Figure 3.9(b)) and target position 4, due to the fact that the target was on the external part of the Kinect field of view, where the depth precision is lower, and at an higher distance from the depth sensor.



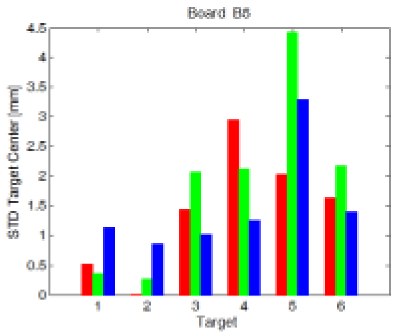
(a)



(b)



(c)



(d)

Figure 3.9 Estimated precision of the Kinect system for the four worst board positions. STD of the spherical target position. With reference to the coordinate system in Figure 3.3, red bars indicate the x coordinate, green bars the y coordinates and the blue bars the z coordinate.

Finally, the RMSDs of the residual errors of the fitting procedure are reported in Figure 3.10. The highest deviation obtained when the board was at pose B4 and B5 for the Optitrack, and at pose B3 for the Kinect, and confirms the results showed in Figure 3.8 and Figure 3.9 and discussed above.

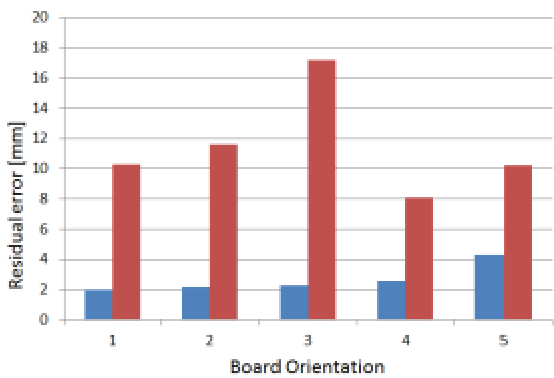


Figure 3.10 RMSDs of residual errors of the fitting procedure of a geometric plane with the six target points location to the six measured locations for the target center, for each board pose. Optitrack data (blue bars) and Kinect data (red bars).

For upper limb tracking, the shoulder and elbow angles are computed for each of the 12 sessions (one circular and one translational motion for the six Kinect configurations). The sample in Figure 3.11 represents the results relative to the circular motion executed by the participant using the end-effector, with the Kinect at the middle down position K3, as defined in Table 3.2. In Figure 3.11(a-d) the variation of the angles $\Delta q_1, \ldots \Delta q_4$, are respectively showed, as obtained from the Kinect and Optitrack joints data, for a circular motion of the end-effector with the Kinect in position K3. Also, in Figure 3.11(f) and (e) the trajectories computed using the Kinect and the Optitrack data are showed, respectively.

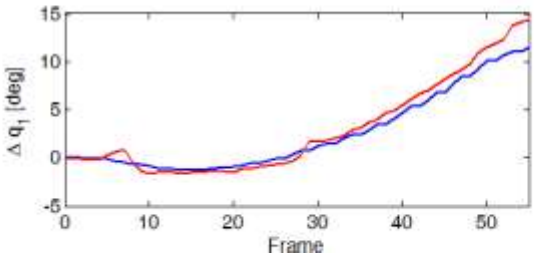
Figure 3.12 illustrates the same information represented in Figure 3.11, but relative to a circular motion captured with the Kinect at the right down position K1, as defined in Table 3.2.

It is worth noting that the parameters of the Kinect and Optitrack body model do not correspond to each other, and this is because of the intrinsic identification of joints location performed by the two systems. This means, in particular, that the arm and forearm length, as identified by the systems, are in general different, and they also vary along the acquisition time. For the Kinect, the identified joints locations are affected mainly by the intrinsic system setting, ambient light and sensor resolution. For the Optitrack, they are affected mainly by the body suit and the reflective marker location. To have a better insight into these effects, Table 3.3 and Table 3.4 reports the mean and STD of l_u and l_f as identified by the two optical systems, for the circular and linear motion of the end-effector, respectively.

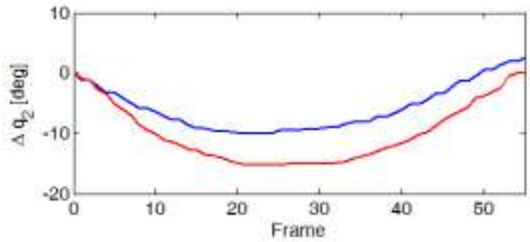
Comparing Figure 3.11 to Figure 3.12, it can be seen that a better match between Optitrack and Kinect data is achieved for the first dataset. Furthermore, the wrist trajectory computed by the Kinect (Figure 3.12(e)) presents some noise due to the high variation in the identification of the forearm and arm lengths, as explained above. In particular, from Table 3.3, it is observed that the STDs of l_u and l_f obtained by the Kinect at the middle down pose (K3), are the lowest compared to all the Kinect acquisitions. The STD of l_u when the Kinect is in position K5 is lower than for K3 but the STD of l_f is greater than for K3. In the middle down configuration, indeed, the subject was completely visible and no joints occlusion occurred during the acquisitions.

In Table 3.5 and Table 3.6 the RMSDs obtained from the angles variations of the Optitrack and Kinect data are reported, for circular motions and linear motions, respectively. The lower trend of these values for middle positions (K3 and K4) of the Kinect confirms that this is the preferable position for the sensor.

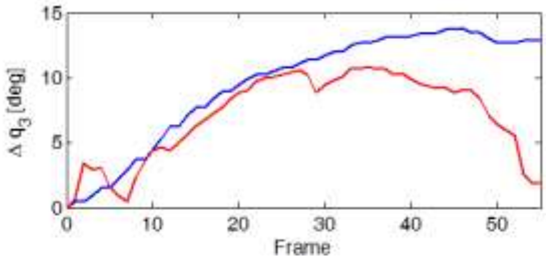
Table 3.7 and Table 3.8 summarize the results obtained in terms of the wrist trajectory for the circular and linear motion, respectively. In Table 3.7 the radius associated to each circular trajectory after circle fitting, and the RoM are reported, while for the linear motion the RoM is reported in Table 3.8.



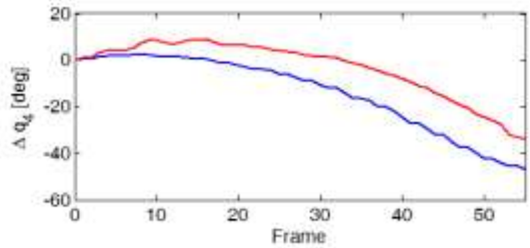
(a)



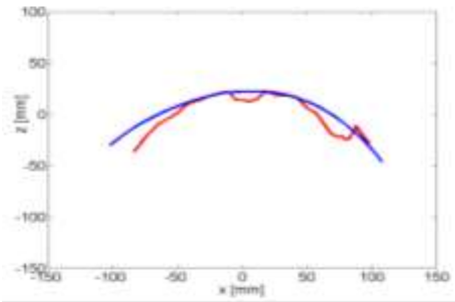
(b)



(c)

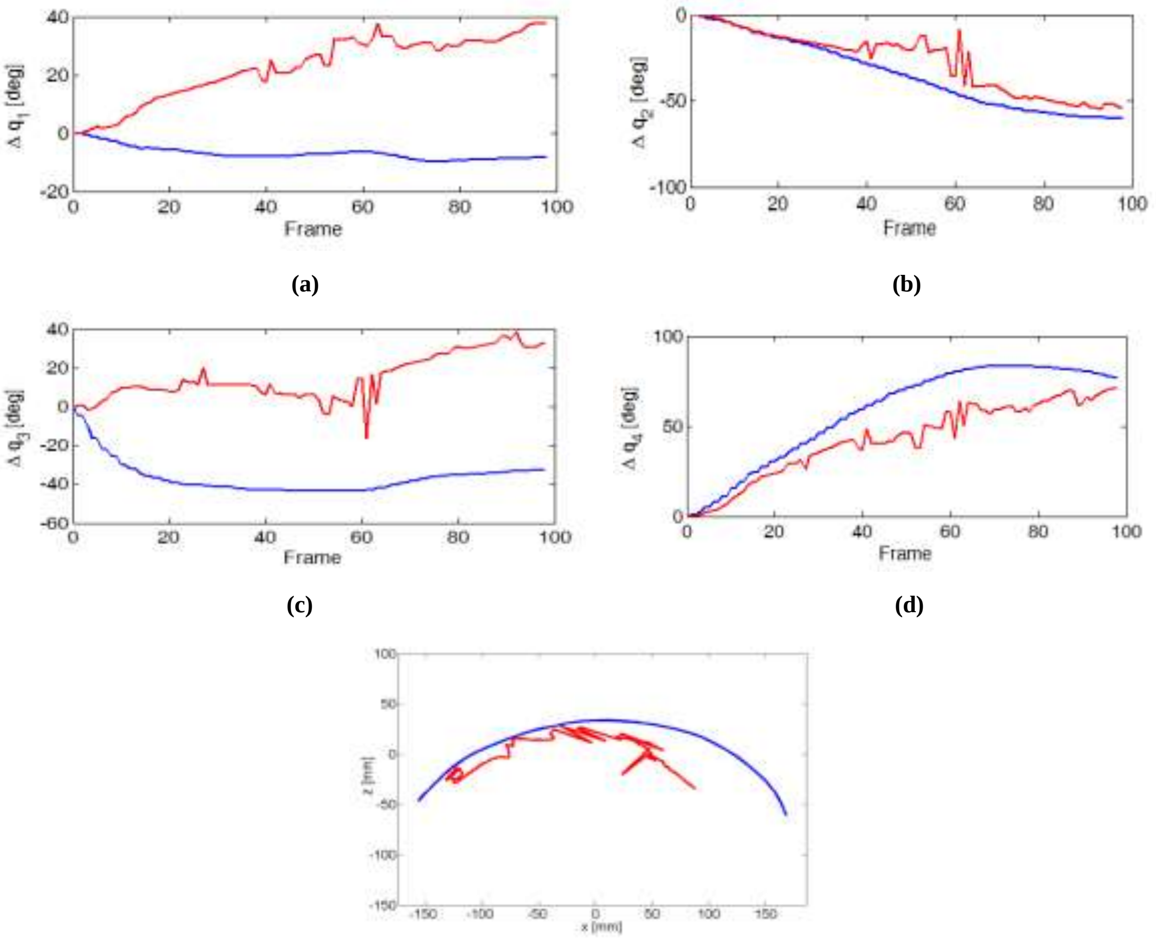


(d)



(e)

Figure 3.11 Results for the circular motion of the end-effector using the right arm, with Kinect in position K3. (a) Δq_1, (b) Δq_2, (c) Δq_3, (d) Δq_4, (e) estimated wrist trajectory by Optitrack (blue lines) and Kinect (red lines). The axes x and z represent the coordinates of the best-fit plane determined on the set of points corresponding to the wrist position during motion.



(e)

Figure 3.12 Results for the circular motion of the end-effector using the right arm, with Kinect in position K2. (a) Δq_1, (b) Δq_2, (c) Δq_3, (d) Δq_4, (e) estimated wrist trajectory by Optitrack (blue lines) and Kinect (red lines). x and z are the coordinate of the best-fit plane determined on the set of points corresponding to the wrist position during motion.

For the circular motions, the mean value of the difference between the radius of the circle fitted on the Kinect data and on the Optitrack data is 42(36) mm, where the value in parentheses represents the STD of the correspondent distribution. Instead, the mean difference between the ROM computed from the Kinect data and from the Optitrack data, is 13(8.3) deg. Finally, the mean difference between the ROM on the linear motion of the hand on the bar is equal to 51.4(33.3) mm.

From Figure 3.11 and Figure 3.12, it is seen that there are some offsets between the angles estimated by the two systems, and this is due to the different body model inherently adopted by the Kinect and Optitrack, as discussed above. For this reason, it is not expected that the angles obtained from the data captured by the two systems are the same. The comparison between the two systems in terms of RoM should be then taken as a qualitative indication only.

Table 3.3 Mean value μ of the arm length l_u, and forearm length l_f identified by the two optical systems along the acquisition frames, for the circular motion and for the different Kinect positions as from Table 3.2. The value in parenthesis is the STD (σ) of the correspondent distribution. The sub-script "K" stands for Kinect, while the "O" stands for Opitrack.

		Circular Motions					
		K1	**K2**	**K3**	**K4**	**K5**	**K6**
***l_u* [mm]**	μ_K (σ)	280.6 (12.6)	204.6 (18.0)	202 (4.4)	224.6 (20.5)	188.1 (2.3)	230.7 (10)
	μ_O (σ)	286.0 (6E-4)	286.0 (7E-4)	276.5 (4E-3)	286 (1E-3)	286 (1E-3)	286 (8E-4)
***l_f* [mm]**	μ_K (σ)	234 (3)	213.5 (18.3)	203.6 (0.8)	215.3 (11.2)	192 (11.1)	223 (8.6)
	μ_O (σ)	285 (7.2)	275.4 (12.0)	252.0 (12.5)	263.2 (9.4)	253.3 (2)	268.5 (9.2)

Table 3.4 Mean value μ of the arm length l_u, and forearm length l_f identified by the two optical systems along the acquisition frames, for the circular motion and for the different Kinect positions as from Table 3.2. The value in parenthesis is the STD (σ) of the correspondent distribution. The sub-script "K" stands for Kinect, while the "O" stands for Opitrack.

		Linear Motions					
		K1	**K2**	**K3**	**K4**	**K5**	**K6**
***l_u* [mm]**	μ_K (σ)	230.5 (11.5)	222.4 (7.7)	248 (4.1)	211 (19.4)	243.5 (6.8)	230.7 (10)
	μ_O (σ)	286.0 (1E-3)	286 (4E-4)	286 (6E-4)	286 (4E-4)	286 (4E-4)	285.8 (9E-4)
***l_f* [mm]**	μ_K (σ)	239.7 (25.3)	216.0 (7)	187.5 (1.6)	232.6 (16.3)	222 (7.2)	223 (8.5)
	μ_O (σ)	274.0 (4.4)	260.4 (8.4)	236.0 (8.2)	243.6 (7.5)	268.2 (14)	268.5 (9.2)

Table 3.5 RMSDs obtained comparing the arm angles variations for Kinect and Optitrack for the circular motions of the end-effector and for the six different Kinect configurations from Table 3.2.

	Circular Motions					
	K1	**K2**	**K3**	**K4**	**K5**	**K6**
RMSD Δq_1	2.5	32.2	6	1.1	5.7	3
RMSD Δq_2	2.0	10.6	3.1	4.5	5.7	4
RMSD Δq_3	20.0	53.0	21.2	4.0	2.6	31
RMSD Δq_4	4.9	17.8	8.4	11.8	3.6	2.7

Table 3.6 RMSDs obtained comparing the arm angles variations for Kinect and Optitrack for the linear motion of the end-effector and for the six different Kinect configurations from Table 3.2.

	Linear Motions					
	K1	**K2**	**K3**	**K4**	**K5**	**K6**
RMSD Δq_1	17.05	7.4	6.7	7.9	3.8	6.7
RMSD Δq_2	16.1	9.2	4.5	1.1	4.5	1.8
RMSD Δq_3	27.7	7.6	8.5	6.0	20.4	32.0
RMSD Δq_4	16.4	5.7	8.4	4.4	7.7	3.7

Table 3.7 Results of the wrist trajectories for circular motion. Circle-fitted radius and estimated RoM, for the six different Kinect configurations as from Table 3.2. The "K" stands for Kinect and the "O" stands for Optitrack.

		K1	**K2**	**K3**	**K4**	**K5**	**K6**
Radius [mm]	**K**	180	102	95.6	118	122	183
	O	179.1	163.3	119.6	201.4	198.7	176.5
RoM [deg]	**K**	105.2	111.7	129.0	96.5	114.3	148
	O	92.3	102.1	121.3	76.8	111.8	173.3

Table 3.8 Results of the wrist trajectories for linear motion. Estimated RoM, for the six different Kinect configurations as from Table 3.2. The "K" stands for Kinect and the "O" stands for Optitrack.

		K1	**K2**	**K3**	**K4**	**K5**	**K6**
RoM [mm]	**K**	234.2	240	263.4	228.5	273.3	293.8
	O	312.2	326	284.9	308.6	292.2	316.9

3.3 Discussion

This chapter presented a preliminary investigation on the expected results and performance that could be obtained when using the marker-less Kinect sensor for abject detection and upper limb motion tracking, with specific application to the rehabilitation of the upper limb. In particular, the aim of this study was focused on the Kinect v2, recently released by the Microsoft. An auxiliary marker-based Optitrack system, composed by 8 cameras and motion capture suit with reflective markers, was used as reference. The object tracking procedure showed that the Optitrack system exhibits a precision and an accuracy higher than that of the Kinect, and this confirmed its use as a reference. The Kinect marker-less system can be used to detect objects in the 3D space with an accuracy close to the centimeter, which can be considered a promising result for object detection and tracking in virtual and enhanced realty applications for upper limb rehabilitation [82]. It is worth noting that, for both optical systems, results were influenced by the position of the object in the field of view of the sensors, but in optimal conditions, i.e. with the target completely observable and in the middle of the field of view, errors lower than the centimeter were obtained with the Kinect and Optitrack.

For the upper limb tracking procedure, a realistic experimental setup was created. A healthy subject (participant) was asked to execute specific motions grasping an end-effector, in order to reproduce a robotic-assisted rehabilitation procedure [54]. It was observed that the Kinect performance are somehow dependent on the position and orientation of the sensor. In order to have a better precision and accuracy, the sensor should be located in front of the subject.

It was observed that the comparison between the two optical systems could only give qualitative indication on the relative precision and accuracy in detecting upper limb tracking. This was related to the inherently different body models implemented in the Kinect and Optitrack software tools. Furthermore, on the one hand the Optitrack data were affected by the presence of the body suit, its fitting to the participant, and by the location and observability of the reflective markers. On the other hand, the Kinect data were mainly affected by the ambient lightning and by the lower resolution of the sensors.

To check the reliability of the body model data, the mean and STD of both the arm and forearm, as identified by the two optical systems along the acquired frames are calculated. It is shown that, when the Kinect is located in front of the subject, the deviations relative to the

arm and the forearm lengths computed by the Kinect were lower, as to suggest that the device is more precise in such configuration rather than in others, where it is inclined respect to the subject. However, the results obtained when the Kinect was in these latter configurations do not dramatically exclude their usability for a qualitative evaluation of the upper limb motion.
It was also observed that, if the upper body of the subject is completely in the field of view of the Kinect and no occlusion of the joints occurs during motion, the body tracking allows to approximate the trajectory of the wrist with lower noise.
However, the estimate of the joints position is not very accurate, as suggested by the STD of segments length computed using the Kinect data. Indeed, comparing the Kinect data with the Optitrack data, as reported in Table 3.3 and Table 3.4, it is possible to note that, for every acquisition step, the Optitrack identifies the length of the upper arm with a very low STD, whereas the Kinect gives different mean lengths for each acquisition step. For the Optitrack data, the mean length of the forearm results to be variable for each acquisition step because of the motion tracking suit, particularly at the wrist.
This preliminary study suggested that the Kinect may be potentially adopted for applications involving upper limb rehabilitation. The advantages of such a system are the low cost, no requirement for calibration, the easy to use and to set up, and the absence of any body marker or suit that could inevitably involve motion artefact. However, the main limitation is the lower resolution, compared to the more expensive marker-based systems. Nevertheless, such resolution, of about few tens of millimeters for the experimental test performed here on the upper limb, make the Kinect an interesting tool for applications in the rehabilitation field, including both object and upper limb tracking procedures.
Future works are aimed at carrying out a more detailed and extensive experimental analysis involving several healthy subjects with different characteristics, trying to come up with a more reliable statistical analysis and some concluding evidence on the usability of the device for the specific body application.

Chapter 4.

Development of a Posture and Upper Limb Position Monitoring Tool using a Kinect sensor.

To regain the functional independence of patient affected by stroke, a rehabilitation activity since the early phase of treatment is necessary. Therefore, the cost of health care services and medications to treat stroke is high. Several methods are developed to reduce therapist intervention and treatment costs and, at the same time, to increase patient access to an intensive and individualized rehabilitation [9]. Without therapist supervision, to motivate the patient and facilitate the recovery process, feedbacks on performance quality must be produced. In the specific context of upper limb rehabilitation, information about upper body posture permit to evaluate if the recovery is correct. Compensatory adaptations and inappropriate postures must be avoided to promote a normal behavior [89].

In this chapter a model to categorize compensatory movements, using data obtained from a Kinect sensor, is presented. An upper limb haptic robotic rehabilitation system for stroke rehabilitation was used to perform simple short scripted motions in the horizontal plane. The model was first tested on a dataset captured using the first version of the Kinect sensor (Kinect v1.0), then a new set of data were recorded, in a new setup and using the last version of the Kinect sensor (Kinect v2.0). The work is part of a project developed at the Intelligent Assistive Technology and Systems Lab – IATSL (Toronto Rehabilitation Institute, University of Toronto), where a period of seven months (January 2014 – July 2014) has been spent, under the title of Development of an Upper Limb Haptic Robotic Rehabilitation System for Stroke Rehabilitation. Collected data includes color (RGB) image sequences, depth image sequences, and a sequence of the 3D coordinates of skeletal joints and upper body parts (e.g. head, shoulders, elbows, etc.).

4.1 Materials and Methods

The objective of this part of the study was to evaluate the usability of the Kinect sensor to categorize compensatory movements. In order to categorize movements a mathematical model that define a relationship between input (joints angles/features) and output (compensations) was built. These relationships were defined thanks to machine learning techniques. The results obtained in previous works [90] [91] suggested to use a supervised learning method. This means that the model is obtained after a "training" phase, during which a "training dataset" is used to teach the model when a compensation occurs. So, the value of the output variable (compensation) for each training sample (joints angle/features) was known.

The training datasets were composed by angles relative to the main segments of upper body, and will be described in the section dedicated to the features. The skeleton data captured by the Kinect were used. Furthermore, to associate to each training sample an output, the color frames were captured. In this way it was possible to look at the pictures and associate a label (model output) to the specific body configuration.

The machine learning model adopted to build the mathematical model was a logistic regression l2-regularized, that will be described later, in this chapter.

Two training datasets were collected, using two different setups. Dataset 1 was recorded using the Kinect sensor v1.0, placed in front of the subject and with the upper body of the subject completely visible to the sensor, as visible in Figure 4.1.

The frames of the Dataset 2 were collected in a new setup, showed in Figure 4.2, and using a Kinect v2.0. The robot used for the rehabilitation protocol is a 2-DOF planar haptic interface, developed by the IATSL in collaboration with Quanser Inc., as shown in Figure 4.2. The robotic tool is specifically designed for intelligent and adaptive post-stroke rehabilitation exercises [32]. It was placed on a table and a monitor was in front of the participant, as illustrated in Figure 4.2. During the protocol for the development of the posture and upper limb monitoring tool, the robot was turned off because it was unnecessary. A Microsoft Kinect was placed behind the table, on the left side of the monitor, and oriented to visualize the participant. The exact placement and height of the Kinect varied for each participant. An example of color frame taken by the Kinect sensor in this setup is showed in Figure 4.3.

Figure 4.1 Setup for Dataset 1. Point of view of the Kinect sensor v1 [91].

(a) **(b)**

Figure 4.2 Robotic tool developed at IATSL. (a) 2-DOF planar haptic interface (b) Set up composed by the 2-DOF planar haptic interface and a computer.

Figure 4.3 A Kinect sensor was placed on the left side of the monitor. A frame taken by the sensor in this configuration is showed. A subject holding the end-effector of the haptic interface, in front of the monitor, and the skeleton tracked by the Kinect are represented.

4.1.1 Dataset

The Dataset 1, collected using the Microsoft Kinect v1.0 and the NITE skeleton tracking library, is described and used in previous works [90], [32].

For the Dataset 2, ten healthy adult subjects without mobility impairments were recruited and asked to reproduce the most common compensations during the execution of short exercises, interacting with the robotic device. The participant sit in front of the robot and executed the motions described below, holding the end-effector:

- Forward and back (left arm and right arm);
- Forward and back with shoulder elevation;
- Forward and back with trunk rotation;
- Forward and back slouching;
- Forward and back leaning forward;
- Reach side to side and back (Left arm and Right arm);
- Reach side to side and back with a trunk rotation.

Each session was recorded with the software Kinect Studio, and an application to extract color images and body information at 30 frames per seconds was used. The main interface of this application is showed in Figure 4.4. It allows to save skeleton data, color, depth and infrared images contemporary. The images can be saved as .png files or as binary files. For each frame the acquisition time was recorded, to guarantee the right alignment between skeleton data and color images. In fact, as visible in Figure 4.4, the time associated to the three types of data represented (skeleton, color image and depth image) and the number of frames per second (FPS), printed under the three images, are not the same.

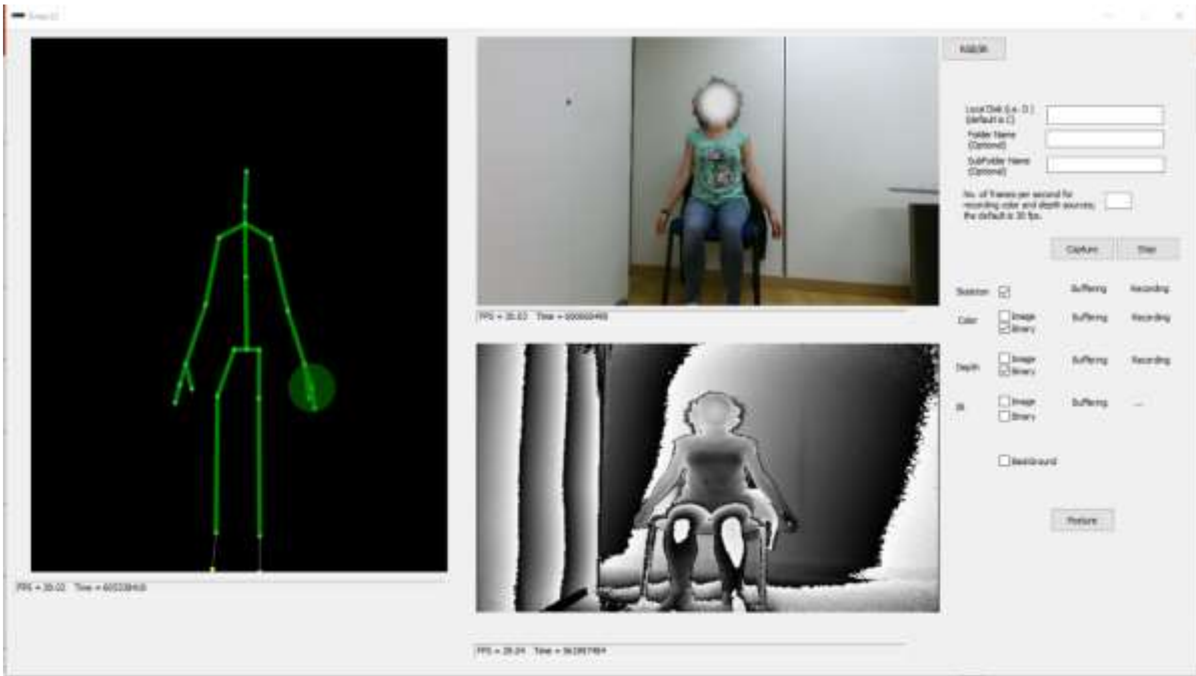
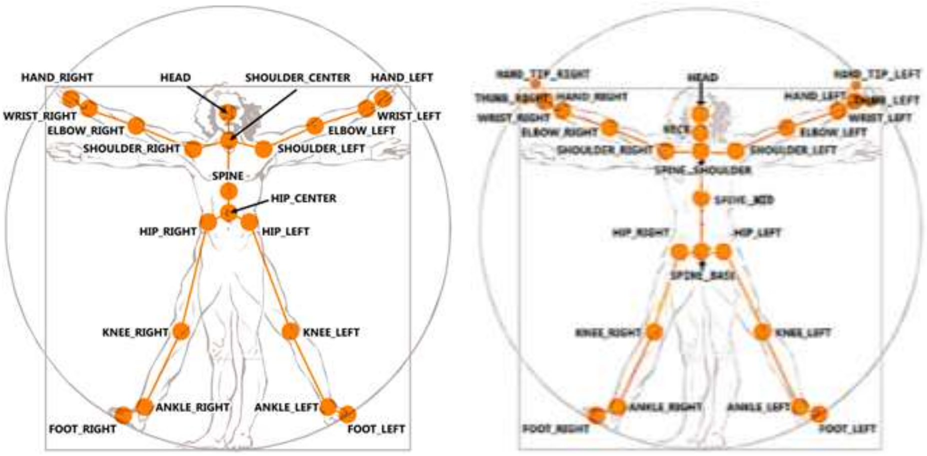


Figure 4.4 Application to save Skeleton, Color, Depth and Infrared frames captured by the Kinect sensor. The folder path can be specified by the fields Local Disk, Folder Name and SubFolder Name. The Color, Depth and Infrared frames can be saved as Image (png files) or in binary files. The image on the left side represent the skeleton tracked by the Kinect. On the right side the Color frame and the Depth frame are showed. For each frame, the frame rate (FPS: frames per second) and the time are specified.

4.1.2 Algorithms

The implementation of a supervised model requires 3 steps: selecting good features and creating a training dataset, model training (learning) and finally, model testing.

The Kinect SDK (Software Development Kit) by Microsoft [5] was used to track the body joints at each frame. These included the 3-D position of neck, spine shoulder, spine mid, shoulders, elbows, and hands (Figure 4.5), all expressed in the coordinate system of the depth camera.



(a) **(b)**

Figure 4.5. Windows SDK body joints (a) for the Kinect v1 and (b) for the Kinect v2

Because of the variations in the sensor pose, a coordinate change was required in order to express the skeletal points in a canonical frame. To do so, at the beginning of each sequence, the subject was asked to sit in front of the robot for a short time. This was considered as *rest pose*. The subject-centered coordinate frame was defined as follows:

$$\boldsymbol{n2} = \frac{\boldsymbol{SpineMid - SpineShoulder}}{\|\boldsymbol{SpineMid - SpineShoulder}\|} \qquad (4.1)$$

$$u = \frac{RightShoulder - LeftShoulder}{\|RightShoulder - LeftShoulder\|} \qquad (4.2)$$

$$n3 = \frac{u\ x\ n2}{\|u\ x\ n2\|} \qquad (4.3)$$

$$n1 = n2\ x\ n3 \qquad (4.4)$$

Where n2 is the unit vector along the line segment connecting the neck to the head point, and define the up and down coordinate, i.e. the y axis in the canonical frame, n1 is the component of the 3-D vector connecting the left shoulder to the right shoulder which was perpendicular to n2 and produced the unit vector along the x axis, indicating the left and right direction. The constraints of an orthonormal frame determined the z axis and its unit vector n3 along the back and forth direction.

4.1.3 Features

The features are the 3-D orientation of the principal line segments, as listed below, expressed as Euler angles:

Dataset 1 (Kinect v 1.0 – NITE)

1. Head – Shoulder center
2. Shoulder center – Spine
3. Left Shoulder – Right Shoulder
4. Right Shoulder – Right Elbow
5. Right Elbow – Right Hand

Dataset 2 (Kinect v 2.0 – Windows SDK)

1. Neck – Spine Shoulder
2. Spine Shoulder – Spine Mid
3. Left Shoulder – Right Shoulder
4. Right Shoulder – Right Elbow
5. Right Elbow – Right Hand

The name of each joint, refers to the joints indicated in Figure 4.5 (a), for the Dataset 1, and Figure 4.5 (b), for the Dataset 2.

The Euler angles $\boldsymbol{e}_i$ for the segment $\boldsymbol{v}_i$ were computed using the following formulas:

$$u_i = v_i/|v_i| \qquad (4.5)$$

$$e_i = \cos^{-1}(u) \qquad (4.6)$$

Three angles were obtained for each segment, so each training sample was composed by 15 values (features).

The goodness of the features for the classification of the compensation modes was previously evaluated in the study conducted by Taati et al., 2012 [91], during which the Dataset 1 was collected. The Dataset 2 was then created using the same features. It is worth noticing that, with the new SDK, the Kinect sensor was able to track new joints of a body, and some of the joints was substituted with the corresponding one tracked by the new Kinect, i.e. the shoulder center joint (Figure 4.5 (a)) with the neck joint (Figure 4.5 (b)).

4.1.4 Training Labels

With the purpose of training the supervised learning model, the training labels had to be generated. An output had to be associated to each training sample, to teach the model which compensation was associated to a specific set of features.

The training labels for the first Dataset, acquired for previous studies [32], [90], were already available, because generated in previous works. To generate the training labels for the second dataset, an application to read binary images was created. Two occupational therapists (human raters) were asked to assign a label to each frame of the sections recorded with the Kinect sensor. The possible labels were five (1,2,3,4,5), associated respectively to the states: *Slouched, Raised shoulder, Trunk rotation, Lean forward, No compensation*. In Figure 4.6 the user interface of the application is showed. It was developed in c# and WPF (Windows Presentation Foundation) [92] and allows the occupational therapist to visualize the frames relative to a session and assign one of the possible labels to each frame. A txt file containing the labels is generated. Looking at the video of the sessions it was observed that more than one compensation could be produced contemporary. For example, the subjects could present an involuntary slouched posture during the simulation of a "raised shoulder" exercise. To track this condition, it was allowed to specify two different labels for a single frame, as visible in the message box in Figure 4.6 b. In Table 4.1 the elements that characterize the user interface, showed in Figure 4.6 are described. Furthermore, the human rater could specify if a new compensation, different than the 5 conditions already highlighted, occurs, writing the name of the compensation in a dedicated text box in the user interface, visible in Figure 4.6 and described in Table 4.1. In this way information about other compensatory motion can be recorded and eventually used for further studies. The labels assigned by the two human raters to the same set of data were compared using the Cohen's Kappa coefficient [93], a statistical measure of inter-rater agreement, defined by the formula 4.7

$$k = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \qquad (4.7)$$

where k is the Choen's Kappa coefficient, Pr(a) is the relative observed agreement among raters and Pr(e) hypothetical probability of chance agreement.

(a)

(b)

Figure 4.6 User interface of the application for the frames annotation. (a) Interface not in use. The numbers are the IDs used to identify the elements in the interface, described in Table 4.1. (b) Interface used by a user (human rater) xxx. In the frame the subject is simulating a Lean forward compensation. In the messages box the number of frames and the posture identified by the user are reported.

Table 4.1 Description of the elements in the user interface of the application for the frames annotation, showed in Figure 4.6. The IDs are the numbers associated to each element in Figure 4.6 a.

ID	Description
0	Text box where the name of the user that is processing the data (human rater) is wrote
1	Buttons of the compensations. Each button corresponds to a compensation. The user can specify which compensation is showed in a frame selecting the corresponding button
2	Text box where the name of a compensation, different than the 5 possible compensations in the section 1, can be specified
3	Button to rewind the frame to the first one
4	Button to go back of just one frame
5	Button to pause the visualization of the frames
6	Button to visualize the frames ad a video
7	Button to go forward of just one frame
8	Button to go to the last frame
9	Check box to specify if the labels associated to the frames must be changed during the visualization of the frames or not. If not, the user can visualize the frames without changing the labels, otherwise, the last labels selected will be associated to all the frames visualized
10	Buttons to speed down or speed up the visualization of the frames
11	Button to browse the folder where the frames are
12	Button to save the labels associated to a set of frames. A txt file will be generated, containing all the labels
13	Buttons to change folder
14	Messages box. Information about the folder selected, the number of frames and the labels associated to the frames are showed in this box
15	Previously saved label files can be loaded. Sing this option the user can continue or review a set of frames already annotated
16	Frame box. The color frames are showed in this box, as in Figure 4.6 b

4.1.5 Training step: application of a Multi-Class Logistic Regression Model

A multi class L2 regularized Logistic Regression Model [94] was used to generate the model that assigns one of the five classes to each frame captured with the Kinect sensor automatically.

Two model were trained: a first model (Model 1) with the features of the Dataset 1 (Kinect v1.0 data) and a second model (Model 2) using the features of the Dataset 2 (Kinect v2.0 data). The Logistic Regression is a simple machine learning training algorithm, usually applied to generate models to separate objects appertaining to different groups. In the simplest case the output of the model can be 0 or 1. In our case the possible outputs were 5, each one corresponding to a different compensation, or to a non compensation state. For this reason, a multiclass model was build. The mathematical model obtained is a classifier that returns the probability that a sample, composed by the features, can appertain to each class. The class with an higher probability will be considered.

The L2 regularization is a technique used by machine learning training algorithms to prevent overfitting and leads to a more generalized model.

A Quasi-Newton Limited Memory Broyden-Fletcher-Goldfarb-Shanno (BFGS) Method [95] was adopted for the optimization of the model and the *no compensation* class was set at 0, in order to avoid over-parameterization.

In this study, the 15 features for each sample were the input of the mathematical model. It returned the maximum value between 5 probabilities, corresponding to the 5 classes indicated. So a model composed by 5 equations was trained, then tested on part of the dataset.

4.1.6 Testing step

The *Leave-one-subject-out Cross Validation* [96] was applied: the model was trained on the data of 9 of the 10 participants and tested on the remaining 1. The same procedure was repeated 10 times, using each time the data of a different participant as testing dataset. The model with the higher accuracy was finally considered. A Normalized Hinton Diagram [97] was used to illustrates the per-frame confusion matrix, in categorizing the five posture modes.

An application to test in real time the classifier was developed. The interface of the application for the Posture Classification is showed in Figure 4.7 and Figure 4.8 (b).

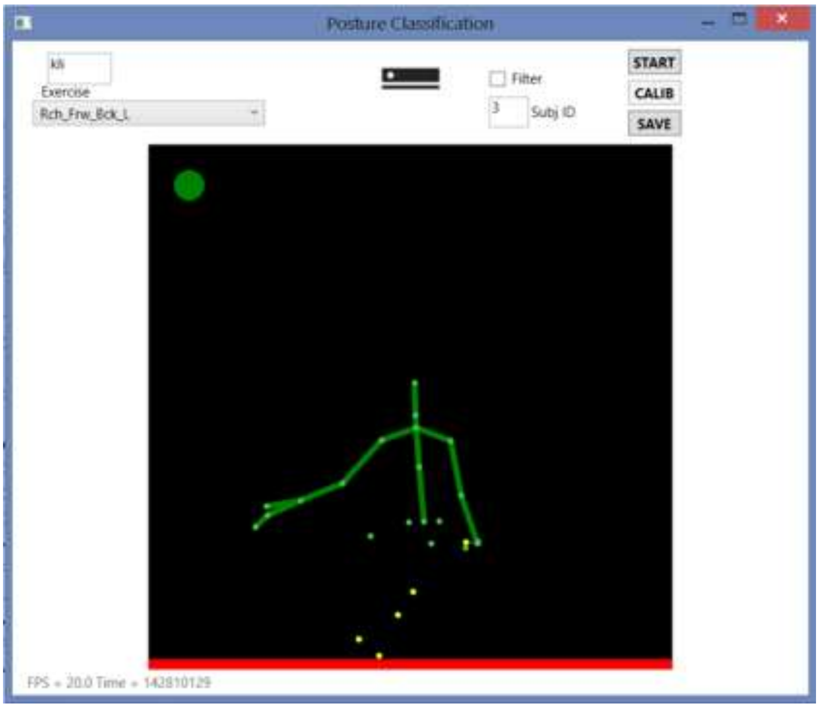
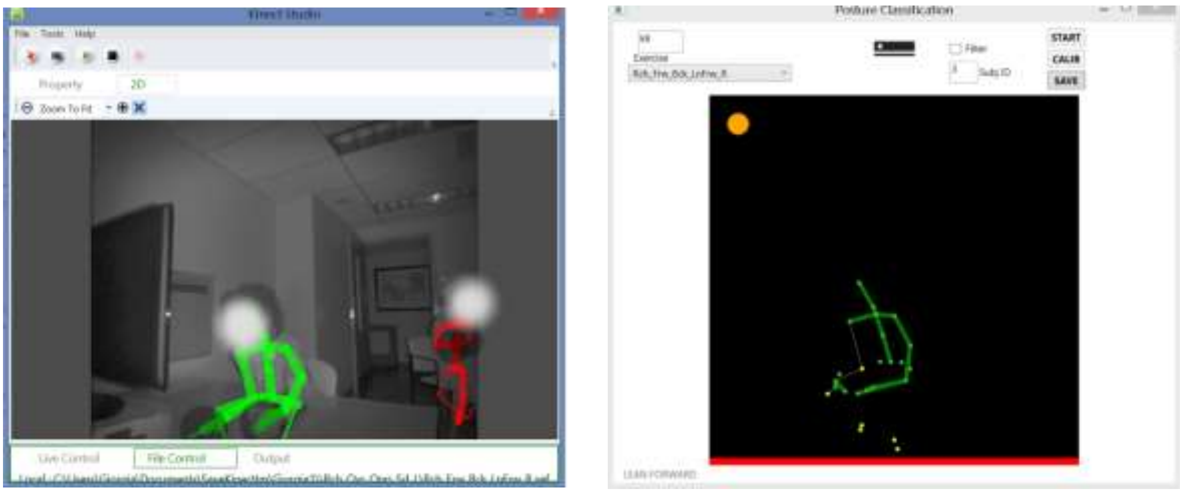


Figure 4.7 Posture Classification application. The application shows the body tracked by the Kinect sensor and a mark on the upper left corner indicate is the subject is compensating or not. The green mark indicates a correct posture, without compensations.



(a) **(b)**

Figure 4.8 Posture Classification application classify a posture as *lean forward.* (a) Kinect Studio application (Microsoft software) that shows the infrared image of the subject of which the posture is classified (green skeleton) and the therapist participating to the study (red skeleton). (b) Posture Classification application interface. The orange mark on the upper left corner of the image and the message on the lower left corner of the interface indicate a *lean forward* compensation. The skeleton of the participant is showed.

Posture Classification reads the data from the Kinect sensor, compute the features as described previously, and classify the posture. First of all, the skeleton id has to be specified. It is possible that more than one skeleton is tracked by the Kinect, so the user has to write in the “Subj ID” field the number associated to the skeleton that will be examined. The IDs are showed on the image before the START button, visible in Figure 4.7 and Figure 4.8 (b), is pushed. After that, the subject should stay in a normal position, in order to allow the calibration procedure, by the CALIB button. Thanks to the calibration phase, the subject-centered coordinate frame can be computed. The features computed by the algorithm and the class associated to each set of features, can be saved by the SAVE button. As visible in Figure 4.7 and Figure 4.8 (b), the skeleton of the participant is showed. The label assigned to the posture for each frame is highlighted by a mark on the upper left corner of the image and by a message on the lower left corner of the interface. If the posture is correct, the mark will be green, as in Figure 4.7, otherwise it will change color. It is possible to specify the name of the User and the name of the exercise that the participant is executing, using the menu Exercise. Finally, a Filter can be applied on the data, checking the box Filter. If the filter is applied, the classification at one frame will be done considering the class associated to the previous frames. In Figure 4.8 an example of Lean forward compensation is reported. In Figure 4.8 (a) the infrared image at a specific time is reported. The skeletons of the participant (green skeleton) and of a therapist (red skeleton) are visible. The Posture Classification application at the same instant is showed in Figure 4.8 (b). The color of the mark is orange and the message on the lower left corner indicate the Lean forward compensation. The participant was executing a Reach Forward and back leaning forward with the right arm, as specified in the Exercise menu with the abbreviation Rch_Frw_Bck_LnFrw_R.

4.2 Results

The Cohen’s kappa coefficient [93], a statistical measure of inter-rater agreement between two human raters (two occupational therapists), on Dataset 2, is $k = 0.88$. The same agreement was reported for Dataset 1 [91]. This result justifies the use of the human rater’s assignments to train the models. In Figure 4.9 The Cohen’s Kappa values for 26 exercises, of which the frames were labeled by two human raters, are reported. The lower values, that results to be under 0.6, corresponds to the following exercises:

Ex. n° 18 – Reach Forward and back Lean Forward, with the Right arm: k = 0.5

Ex. n° 19 – Reach Forward and back Trunk Rotation, with the Left arm: k = 0.42

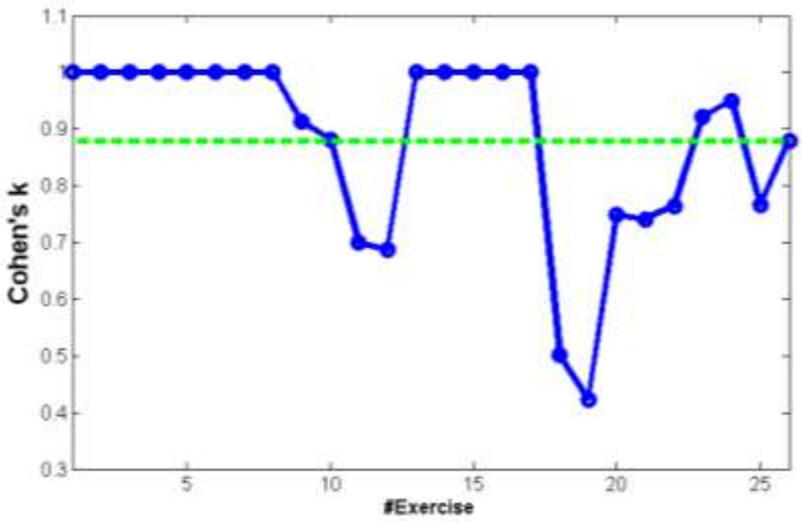


Figure 4.9 Cohen's Kappa on a set of 26 different exercises. It is the statistical measure of inter-rater agreement between two human raters (two occupational therapists) for each exercise.

In Figure 4.10 the labels assigned by the two human raters to the frames of three exercises are compared. Each line of the arrays represents a label and the two arrays are relative to two human raters. The green lines indicated a "no compensation" state. The compensations are represented by other colors: pink indicates the Lean Forward compensation, and blue the Trunk Rotation. Figure 4.10 (a) and (b) show the exercises for which the Cohen's k is lower: Reach Forward and back Leaning Forward, with the Right arm and Reach Forward and back with Trunk Rotation, with the Left arm. In both of them, it is possible to notice a different selection, by the two human raters, of the starting and ending frames of the compensations. Furthermore, in Figure 4.10 (b), the human rater 1 assigned a Lean Forward compensation at the initial frames of the session. This differences influenced the result in terms of Cohen's k. In Figure 4.10 (c) an exercise without compensation is represented. All the lines of both arrays are green, so both the human raters didn't see any compensation during the exercise, and the Cohen's k is equal to 1.

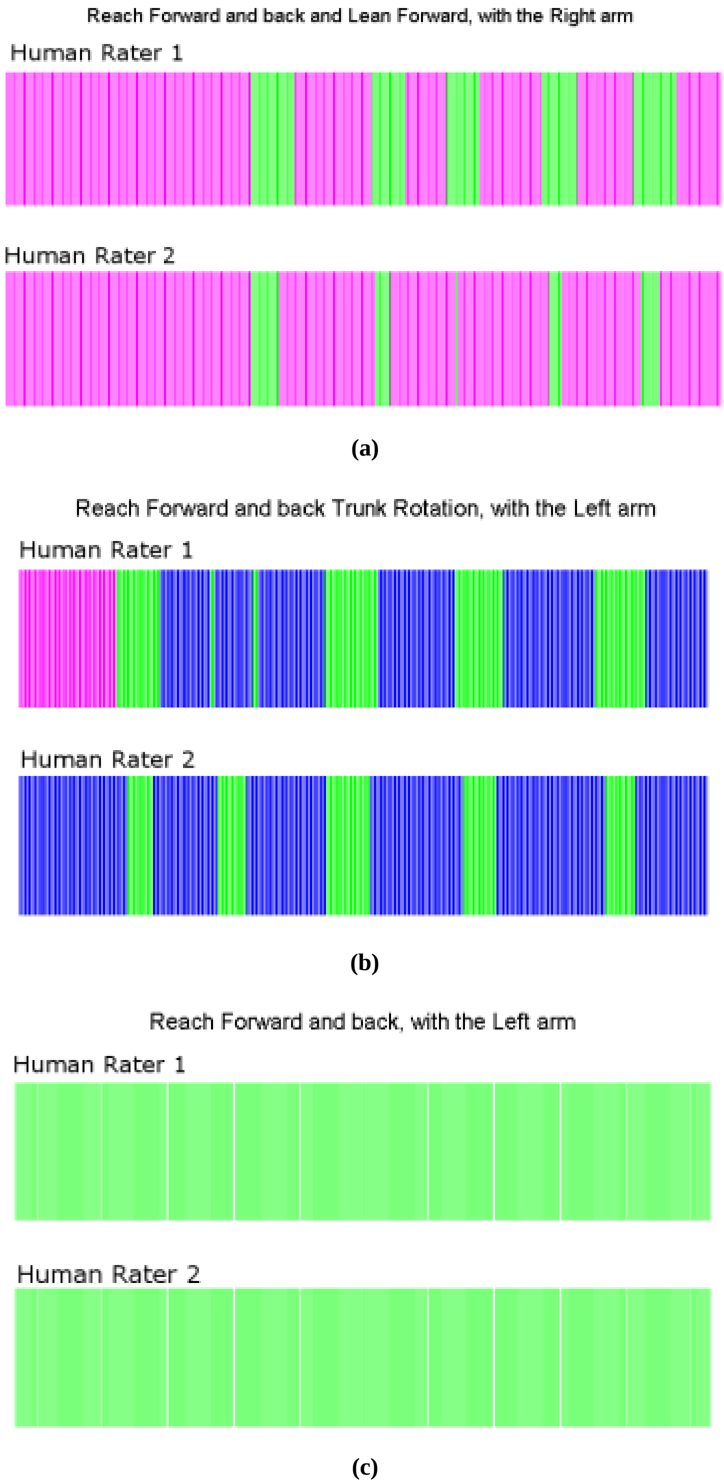


Figure 4.10 Comparison between labels assigned to different exercises by two human raters (occupational therapists). Labels assigned to frames relative to (a) Reach Forward and back - Lean Forward, with the Right arm; (b) Reach Forward and back - Trunk Rotation, with the Left arm; (c) Reach Forward and back with the Left arm.

A Leave-one-subject-out Cross Validation was applied [98]. The accuracy of *Model 1* is 95%. The accuracy of *Model 2* is 84%.

In Table 4.2 and in Table 4.3 the confusion matrixes obtained comparing the classes associated by the models and the classes indicated by the human rater, are reported. These confusion matrixes are also represented as normalized Hinton Diagram in Figure 4.11. The rows and columns indicated the compensations in the order: 1- Slouched, 2- Raised Shoulder, 3- Trunk Rotation, 4- Lean Forward, 5- No compensation.

The confusion matrixes are n x m matrixes, where the values on the principal diagonal are the numbers of test samples classified correctly by the model (the class evaluated by the model is the same than the human rater class). The values outside the principal diagonal, are the number of test samples incorrectly classified (the class evaluated by the model is different than the human rater class). For example, in Table 4.2 is specified that 32 test samples (row 1, column 5) were classified as appertaining to the 5th class (id of the column), No compensations, by the model, but they should be classified as appertaining to the class 1 (id of the row), Slouched.

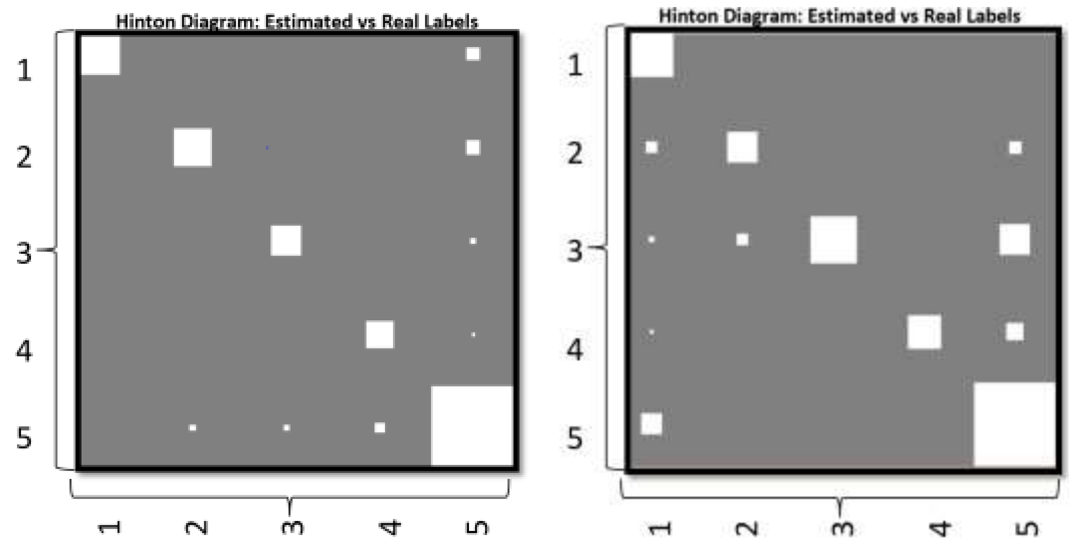
The confusion matrix relative to *Model 1* (Table 4.2 and Figure 4.11 (a)) shows that the higher percentage of test samples incorrectly classified by the *Model 1* were interpreted as appertaining to the class *No compensation*. Indeed, the confusion matrix relative to the *Model 2* (Table 4.3 and Figure 4.11 (b)) presents more values classified, incorrectly, by the model as appertaining to the class *Slouched*.

Table 4.2 Confusion matrix representing the results of *Model 1*. The values reported on the diagonal of the matrix are the number of samples classified correctly. The values outside the diagonal represent the number of samples classified as appertaining to the class m (column id) by the model, but labeled as appertaining to the n (row id) class by the human rater. The classes are ordered as: 1 Slouched, 2 Raised shoulder, 3 Trunk rotation, 4 Lean forward, 5 No compensations.

	1	**2**	**3**	**4**	**5**
1	329	0	0	0	32
2	0	271	0	0	36
3	0	0	164	0	6
4	0	0	0	136	2
5	0	7	7	18	1286

Table 4.3 Confusion matrix representing the results of *Model 2*. The values reported on the diagonal of the matrix are the number of samples classified correctly. The values outside the diagonal represent the number of samples classified as appertaining to the class m (column id) by the model, but labeled as appertaining to the n (row id) class by the human rater. The classes are ordered as: 1 Slouched, 2 Raised shoulder, 3 Trunk rotation, 4 Lean forward, 5 No compensations.

	1	**2**	**3**	**4**	**5**
1	322	0	0	0	0
2	24	159	0	0	27
3	5	21	382	0	158
4	2	0	0	191	51
5	77	0	0	0	1177



(a) (b)

Figure 4.11 Normalized Hinton Diagrams for (a) model trained with the Dataset 1 and (b) model trained with the Dataset 2. The labels evaluated by the model are compared with the real labels. The white squares are a representation of the number of frames labeled as appertaining to a specific class. The numeric matrix corresponding to (a) and (b) are respectively reported in Table 4.2 and in Error! Reference source not found.**.**

The lower accuracy of Model 2 could be justified by the setup, that is different than the one used collecting the first dataset. With the second setup, the spine_base, that is the root joint for the Kinect skeleton, is not visible, instead it was visible with the first setup. Furthermore, in the first setup the Kinect was placed in an optimal position. In fact, it was in front of the subject. This configuration was not possible in the second setup, where the Kinect was placed on a side of the table. This configuration was necessary to permit the tracking of the upper body of the subject. Differing from the first setup, that was a preliminary setup, the second one was composed by larger monitor and by a table that supported the arm of the patients in all the possible positions. These conditions had determined the position of the Kinect sensor in the second setup. In Chapter 3 it was described how the accuracy of the tracking obtained with the Kinect sensor is influenced by the position of the sensor relative to the body to track. It was demonstrated that the frontal position was the optimal one and that a lower accuracy was reported when the Kinect sensor was placed not in front of the subject. These observations justify also the higher number of test samples classified as appertaining to the *Slouched* class by the *Model 2*. In fact, because the bad tracking of the spine_base joint, the trunk orientation showed an higher inclination than the real one, influencing the classification.

4.3 Discussion

The effectiveness of the Kinect data for the automatic classification of compensations was evaluated. A classifier that analyzes the data of this low cost and easy to use sensor, can be advantageous for the development of systems dedicated to the recovery of normal motor abilities. During an experience at the IATLS (University of Toronto) the study of the Kinect for Windows to monitor the posture of a group of healthy subject was conducted.

A L2 regularized Logistic Regression Model was trained and then tested on data relative to healthy participants, that simulated the most common types of compensations usually adopted by stroke patients: Slouched state, Raised Shoulder state, Trunk Rotation and Lean Forward state. Two datasets were used: the first one obtained using the Kinect v1.0 and the second one using the Kinect v2.0. Then, two different models were trained. Comparing the accuracy of the classification executed with the two models, it was highlighted the fact that the location of the Kinect sensor can influence the classification. In fact, the model trained with the Dataset 1, captured with the Kinect v1.0 placed in front of the participant, and without objects that could occlude the lower part of the body, presented an higher accuracy than the model trained with the Kinect v2.0. The Dataset 2 was captured in not optimal conditions, due to the complete setup, used for the rehabilitative session with the robot.

Chapter 5.

Interactive design of patient-oriented video-games for rehabilitation: concept and application

Virtual reality (VR) is becoming a popular tool in physical therapy and in the rehabilitation field. It offers the opportunity to transform the traditional therapy into a funny experience, where patients can train their motor and cognitive skills [48], [71], [99]. Games market, and new technologies in general, give to the rehabilitation field a relevant contribution with several devices that can be used to track the motion of a human subject and interact with a virtual environment [100]- [101]. One example is the Kinect™ by Microsoft [102]. Other devices, such as webcams tracking coloured markers [103], [104], Nintendo Wii [105]or Nintendo WiiFit Balance Board [106], are also used as interactive tools in rehabilitation games. However, those devices are able to track few body joints and do not allow to reproduce the motion of the entire body of the patient. Such a limitation is overtaken by the Kinect™, making it an advantageous sensor – and this has motivated its use in the present work.

Looking at previous experiences in the rehabilitation field, it is evident the important role of both the patients and of the therapists for the development of rehabilitation systems [107]-[108]. In particular, the role of the patient is an overall assessment of specific difficulties, interest and motivation encountered in its use [99], while the role of the therapist is to evaluate the specific features of the system to allow the appropriate definition of a therapeutic plan [99]. The majority of the existing systems are designed and tested on a specific set of patients affected by the same pathology, limiting their use to that specific group only [102], [103], [105], [107], [109], [50]. The rehabilitative video-games are usually organized in levels, that differ for the difficulty of the tasks [103], [110]. Automatic algorithms, for the evaluation of the patients performance, can be applied to adapt the difficulty of the game, allowing the patient to complete the tasks [100]. They are prone to be used for pathology-oriented video-games, since they work better when applied to track specific categories of behaviors and rehabilitation movements [111]. The automatic assessment of the patient performance can be substituted by the intervention of the therapist [110], [112], who can properly set a series of game parameters depending on the specific patient. This approach is more prone to be used with a patient-oriented video-games, where a much wider range of behaviors and rehabilitation movements are expected. The therapist can thus manually adapt the therapy in order to maintain the active participation of the patient and guarantee positive feedbacks, allowing the patient to complete the tasks preventing fatigue [108], [113]. In this study, a patient-oriented rehabilitation approach is followed with a manual assessment by the therapist, who can set the game level according to the patient ability.

Rehabilitative games are usually implemented by the definition of functional tasks, which induce the subject to execute a desired complex movement. Reaching [114], swaying [115] and balance tasks [103] are often implemented. Most of them can be effectively realized by inducing the patient to 'reach' a specific target with parts of the body. For example, by the reaching approach it is possible to induce the patients increasing the workspace of lower and upper limbs [116], [76], asking them to reach a target, or testing and improving their dynamic balance and trunk control [103]. Reaching games will be considered in this work as an effective way to realize a variety of different functional tasks.

Based on the motivation discussed above, this work proposes the concept and application of a system for the interactive design of rehabilitative patient-oriented video-games based on the use of the Kinect™. The main idea, which makes it different from other existing systems [102], [103], [105], [107], [109], [50], is (i) the possibility to adapt the game design to patients affected by different types of pathologies and (ii) the possibility for the therapist to design the tasks characterizing the game and its rules.

The system has been developed in collaboration with ANMIC, a highly specialized rehabilitation center in Crotone (Italy), and tested by three therapists of this rehabilitation center. Trunk control and shoulder motion rehabilitation were considered as application examples, as these are of interest to patients affected by different neurological disorders, such as stroke [117], [118], Parkinson's disease [47], [119], [120], [121] multiple sclerosis [116], [76], [122], [47], or after specific surgery. This allowed to test the system with a heterogeneous group of patients.

5.1 Materials and Methods: General Concept

The system presented in this chapter allows the therapists (on the base of their expertise and clinical experience) to design the rehabilitative tasks through a user-friendly software application, the setting interface, while allowing the patient to interact with a virtual scenario through an avatar to reach a target. In particular, the therapist is in charge of defining the rules of the game, choosing the main parameters which affect the type of motion required by the patient, the speed of action and the constraints of movement. The motion of the patient is tracked by the Kinect™ sensor and reproduced by an avatar in a virtual environment. Thanks to the full body tracking allowed by the Kinect™, the system can be used to implement rehabilitative games that can involve several parts of the body, e.g. upper limbs, lower limbs, trunk.

One personal computer (PC), two screens and the Kinect™ sensor are required. One screen is used by the therapist to control the game settings, monitor the game session, the patient performance and save/retrieve data. The PC is used to run the software application developed here for the game design, and to control the Kinect™ acquisition. This latter is located in front of the patient, at a distance of approximately 1.5m, and it is used to track his/her body motion. The second screen is also located in front of the patient and it is used as a virtual mirror. A schematic representation of the whole system is illustrated in figure 1(a) and the real setup adopted for this study is shown in figure 1(b).

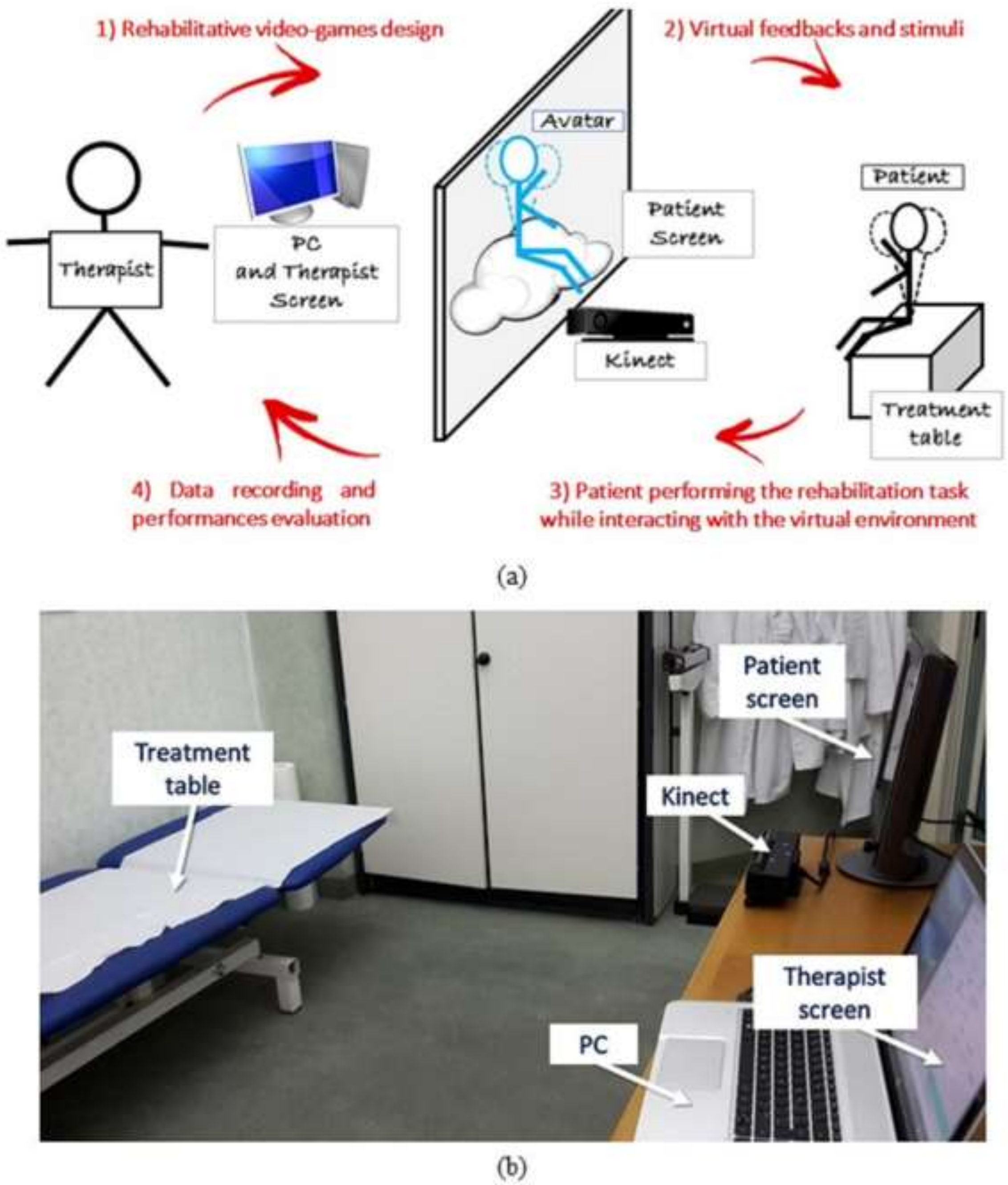


Figure 5.1 Setup used for the tests: (a) schematic representation, and (b) real configuration.

The parameters set by the therapist (through the setting interface) to design the rehabilitation task are described in table 1. They are grouped in four different typologies: patient posture, game visualization, target features and reaching options. Those parameters will affect the game characteristics, its level of difficulty and the action/movement to be undertaken by the patient.

Table 5.1 Description of the options available in the setting interface.

Options		Description
Patient posture		
1	Calibration	Records the normal position of the patient that will be the reference for posture evaluation
2	Tolerance	Quantifies how far the patient can move out from his calibration posture
3	Motion side	Defines whether the left, right or front movements are allowed
4	Legs position	Defines whether the patient knees should be closed, halfway or wide-open
5	Hands position	Defines whether the patient can or cannot use hands to balance the required movement
Game visualization		
6	Views	Defines the view-point for the main 3D scene
7	Second camera	Defines whether to show an auxiliary view-point to help identification of the 3D scene
Target features		
8	3D coordinates	Define the x, y and z coordinates of the target
9	Size	Defines the size of the target
10	Speed	Controls the speed of the moving target
11	Random positions	Defines the possibility to generate random positions for the target
12	Recorded positions	Defines the number of target positions displayed in the game
13	Number of repetitions	Defines the number of times a specified target position is kept and repeated
14	Static/In motion target	Defines whether the target appears in a fixed position or as a moving object
Reaching options		
15	Body parts	Defines which part of the body the patient has to use to reach the target
16	Bimanual mode	Defines whether the patient has to reach the target with both body parts simultaneously

Within the options for posture control, of particular importance (as detailed in the next section) is the calibration option, by which the therapist can set the correct posture of the patient for performance evaluation – the calibration is executed at the first stage of the game, and a threshold tolerance may be specified as well. A set of options are available to control the 3D visualization of the game – those will allow to choose the proper view-point for the specific exercise and even to activate a second auxiliary view to help the patient familiarizing with the

3D visualization. A series of options are devoted to the target specifications – the therapist defines the sequence of exercises to be executed during the rehabilitation session, and is thus able to control the position, dimension, number and velocity of a target, as well as the time duration of each session and the number of repetitions, as these latter showed encouraging results in rehabilitation [123], [124]. Using one or more targets in the virtual environment, several exercises can be implemented, and they can involve different parts of the body (upper limbs, lower limbs or trunk). The therapist defines the parts of the body that the patient is asked to use to reach the target and accomplish the specific rehabilitation task, through the reaching options in table 1. For instance, it is possible to ask the patient to reach (or avoid) a target with the hand or the elbow, to rehabilitate the elbow articulation or the shoulder articulation [104]. Moreover, it is possible to reach a target with the shoulder or the hand, or more targets simultaneously with both shoulders or hands, to rehabilitate the trunk control and the balance ability [105]. Lower limbs can be trained as well for rehabilitation, where one or more targets can be used, for instance, to stimulate sitting knee extension, squats, standing knee extension, hamstring curl, hip abduction in standing, and hip extension in standing [104]. Different scenarios can be included, and those should be developed in collaboration with clinicians, in order to present suitable graphics and feedbacks, which can be stimulating for the patients. The two scenarios adopted in this work, the setting interface and its game parameters were developed with the collaboration of a therapist.

5.2 Materials and Methods: Applications

During the implementation and validation of the system, attention was focused on trunk control and shoulder motion rehabilitation. For those applications, two different scenarios of reaching games [110] have been proposed. The scenarios were developed by an engineer in collaboration with a therapist for the definition of the rules of the game: they will be referred to as “Reach the Apple” and “Keep the Ball” scenario. Both of them could be used to train the trunk or the shoulder motion, depending on the settings chosen by the therapist, and are designed to be graphically simple and effective, so that the patient can focus more on the goal to accomplish rather than on the environment details. Figures 2(a) and (b) show screen-shots of the two different scenarios. The adoption of different scenarios to train and rehabilitate similar parts of the body is suggested by motor learning theory [101] – the aim is to maintain the patient active and concentrated during the rehabilitation session.

Figure 5.2 Different scenarios proposed for the video-game: (a) "Reach the Apple" and (b) "Keep the Ball". In both scenarios, a vertical red line is used as a reference to better identify the target position.

Since the two scenarios are similar in their concept, the "Reach the Apple" scenario will be taken as a reference from now on. As mentioned in Section 2, the patient is represented by an avatar, and is asked to reach an apple in the 3D environment. The patient is seated on a chair or treatment table, and so is the corresponding avatar, as visible in figure 3, and in videos 1 and 2. Figure 3(a) shows the position of the subject performing the motion, as captured by the Kinect™ sensor as a colour image, while figure 3(b) shows the corresponding position of the avatar in the virtual environment. The patient can be asked to reach the target using different parts of the body, as mentioned earlier, and bimanual mode can also be activated where the patient is asked to reach the target with two hands (or body parts) simultaneously. The body part (or parts) selected by the therapist are highlighted on the avatar, as shown in figure 3(b), where the selected body part is the hand.

Figure 5.3 A frame captured during the execution of the "Reach the Apple" game: (a) KinectTM frame and its corresponding VR representation (b). An auxiliary view of the game is showed on the top-right corner of the main screen in (b).

The apple-target may appear statically on the position decided by the therapist, or may be set to motion from one desired position to another one. In the "Keep the Ball" scenario, the patient has to detect the trajectory of the kicked ball-target, and try to keep it – the specific trajectory is defined by the therapist:

If the patient moves in a direction that is "not allowed" by the therapist, as in figure 4(a), a phantom avatar appears on the VR scene showing the posture recorded during the initial calibration phase, as shown in figure 4(b), and an arrow on the screen suggests the proper direction towards which the subject has to move in order to perform the exercise correctly. The allowed motions may be specified by the therapist using the options for posture control in table 1. The therapist is also able to decide not to allow the patients to be supported by their hands during a specific exercise. In particular, if the wrists of the patient are identified to be at a distance from the treatment table greater than that specified during the calibration phase, a visual feedback suggests the patient to lift the hands, as illustrated in figure 5. The therapist is also able to control the position of the legs of the patient, since these can affect the patient balancing during the exercise. Knees can be thus specified to be closed to each other, as in figure 6(a), halfway, as in figure 6(b) or wide-open, as in figure 6(c), depending on the patient ability and on the specific exercise to be performed. Through the game visualization options, the therapist is able to change the point of view of the scenario, and thus showing the avatar from the left, right, top, front and back view. To facilitate the 3D visualization of the game, a second camera can be activated and an auxiliary point of view can be displayed in the top-right corner of the patient screen, as shown in figure 3(b).

Through the target feature options, the therapist is able to decide whether is better to have a dynamic target, moving from one point to another, or a static target, which appears directly at a specified and fixed position. The size and the speed of the target can be controlled as well.

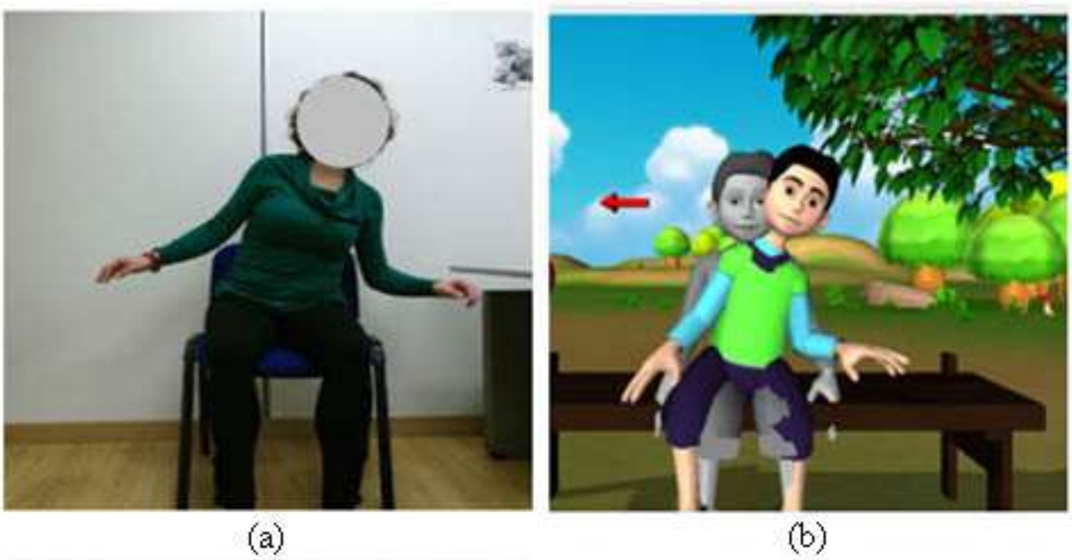


Figure 5.4 . Avatar and phantom in the "Reach the Apple" game. The subject is moving on the right side but the target (apple) is on the left side (not shown here). (a) Actual position of the subject, and (b) corresponding shadow phantom, which indicates the reference position. The red arrow in (b) indicates the direction where the subject is asked to move

Figure 5.5 Hand contact detection on the treatment table. (a) Actual position of the subject: left and right hands are touching the chair. (b) Corresponding configuration of the avatar. The two arrows in (b) indicate that both hands should be lifted, as they are touching the chair.

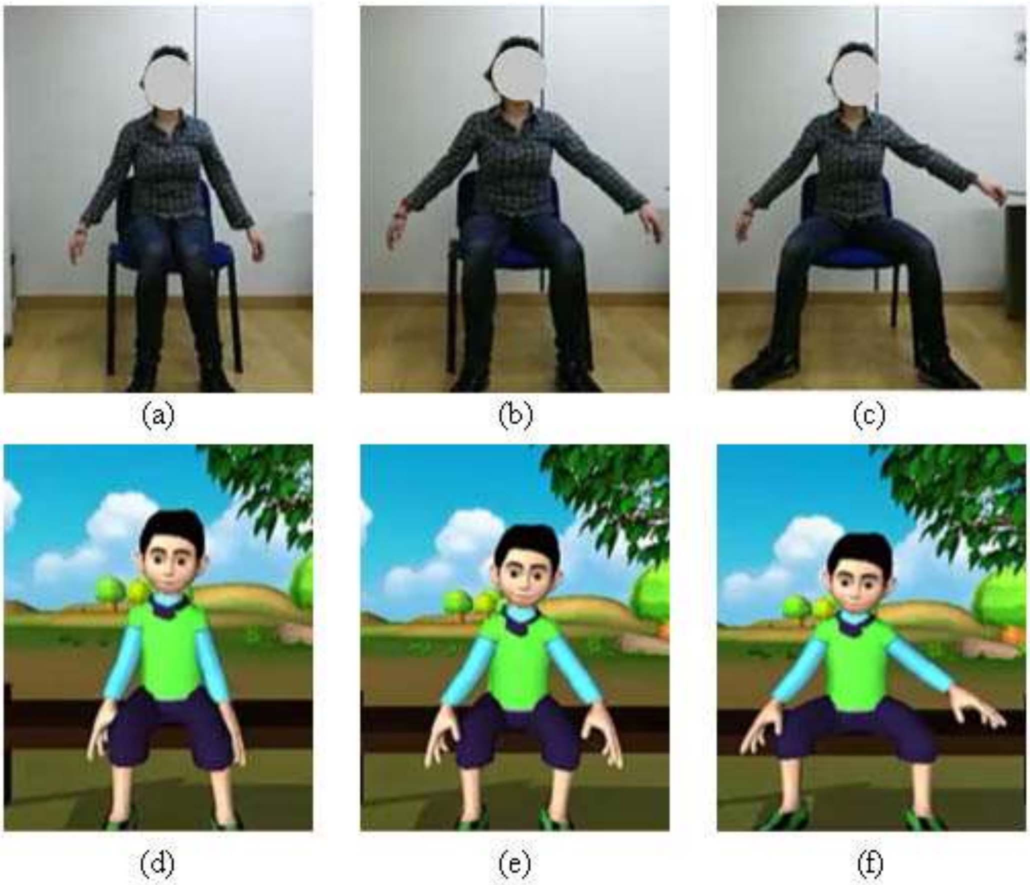


Figure 5.6 Screen-shots illustrating legs control. Subject with legs (a) closed (b) halfway, (c) wide-open. Parts (d), (e) and (f) show the avatar configuration corresponding to the subject in (a), (b) and (c), respectively.

In order to evaluate the patient appreciation for the video-games, two questionnaires were proposed to the patients. The questionnaires were taken from the Game Experience Questionnaire (GEQ) developed and validated by IJsselsteijn et al. [107]. The first one, referred to as the In-Game questionnaire, was filled in during the second session – it was used to investigate the feel of competence, the immersion of the patient in the game, the flow of the game, the feel of tension, the feel of challenge, the negative effect, and finally the positive effect of the game on the patients. The In-Game questionnaire is reported in table 2, where the questions are grouped into seven specific categories. The second questionnaire, referred to as the Post-Game questionnaire, was filled in at the end of the sessions and consisted of four categories of questions aimed at evaluating the "return back to realty", the tiredness of the patient at the end of the game, and any negative or positive experience. The Post-Game questionnaire is reported in table 3.

Table 5.2 In-Game Questionnaire.

Tension
I felt frustrated
I felt irritable
Positive affect
I felt content
I felt good
Negative affect
I felt bored
I found it tiresome
Challenge
I felt challenged
I had to put a lot of effort into it
Flow
I forgot everything around me
I felt completely absorbed
Immersion
I was interested in the game's story
I found it impressive
Competence
I felt successful
I felt skillful

Table 5.3 Post-Game Questionnaire.

Returning to Reality
I found it hard to get back to reality
I felt disoriented
I had a sense that I had returned from a journey
Tiredness
I felt weary
I felt proud
Negative Experience
I felt bad
I felt guilty
I found it a waste of time
I felt that I could have done more useful things
I felt regret
I felt ashamed
Positive Experience
I felt revived
It felt like a victory
I felt energized
I felt satisfied
I felt powerful
I felt proud

Table 5.4 Answers associated to the questions of the provided questionnaires.

Answer	not at all	slightly	moderately	fairly	extremely
Score	0	1	2	3	4

The patients were asked to respond to each of the questions in the GEQ according to the five-point Likert scale [108] reported in table 4, where each answer have been conveniently associated to a numeric score from 0 to 4.

In order to validate the usability of the system, it was tested by three therapists. The first therapist was assigned to three patients, the second one was assigned to one patient and the third one was assigned to two patients. Each patient was involved in two sessions of 40 minutes each. They volunteered to the study and signed informed consent for enrolment. The therapists were previously trained on the use of the software and then assisted by an engineer (who was involved in the system development) during all the sessions.

5.3 Results

The information about the subjects involved in the test is shown in table 5. It can be seen that the average age is 67 and that they were affected by different disorders. During the twelve rehabilitative sessions the three therapists and the six patients showed interest in the system. The patients did not have previous experiences with video-games based on motion tracking devices, or virtual reality immersion at all. During the first session, all of them showed more difficulty in reaching the target than in the second session. Depending on the specific disability of the patient, they felt tired at the end of some tasks.

The system was used as a support to the traditional rehabilitative session. The advantages of such an approach were, on the one hand, that the therapist was in charge of inducing the patients to execute a specific motion through the support of the video-game, and on the other hand, that the therapist was able to adopt traditional tools to improve the rehabilitative experience, such as a support for the feet or a ball to constrain the position of the legs. The manual setting of the target allowed the therapists to define several typologies of exercises, depending on the ability of the patients and their pathology. In particular, by the selection of the part of the body that the patient had to use to reach the target, the therapists could focus more on the control of the trunk or on the motion of the shoulders.

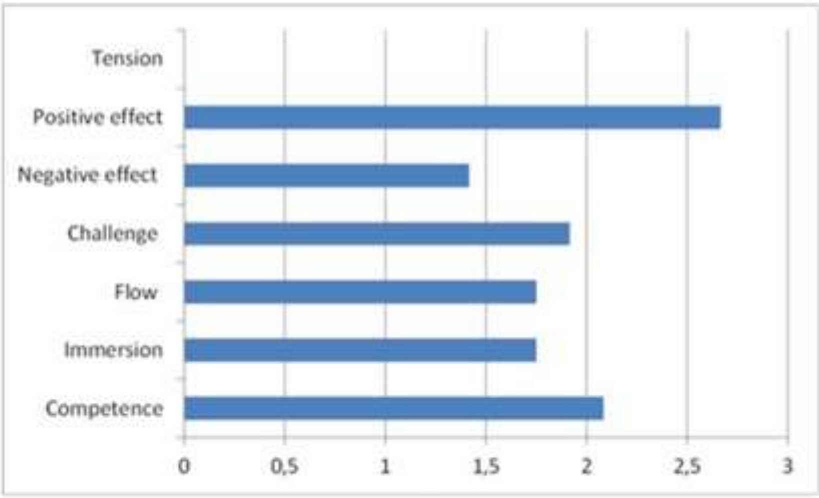
The “Keep the Ball” scenario was run at the end of each session. The patients showed more difficulty in reaching the target than in the “Reach the Apple” scenario because the target was moving faster. However, the former scenario resulted to be more engaging for the patients, since they focused their attention more on the task (keeping the ball) than on the execution of a specific or prescribed motion.

An evaluation of the patients experience was achieved by the GEQ. Figures 7(a) and (b) summarize the results of the In-Game and Post-Game questionnaire, respectively. Each bar corresponds to a category of questions, and the associated score is the average value of the scores of the questions in the category achieved by the whole group of patients.

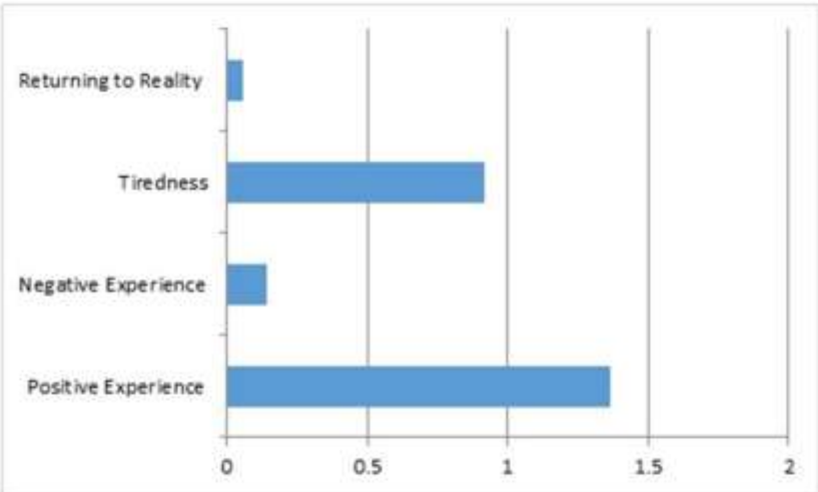
In figures 8(a) and (b) results are reported for each patient, and the indication of the corresponding therapist is also highlighted. In particular, each bar corresponds to a patient and three different colors are used to highlight the therapist who assisted the patient.

Table 5.5 Subjects volunteering the study.

ID	Sex	Age	Diagnosis
1	F	61	Multiple Sclerosis
2	F	57	Multiple Sclerosis
3	M	66	Ictus
4	M	73	Right sided hemiparesis due to an herniotomy
5	F	73	Ictus
6	F	72	Cerebellar ataxia

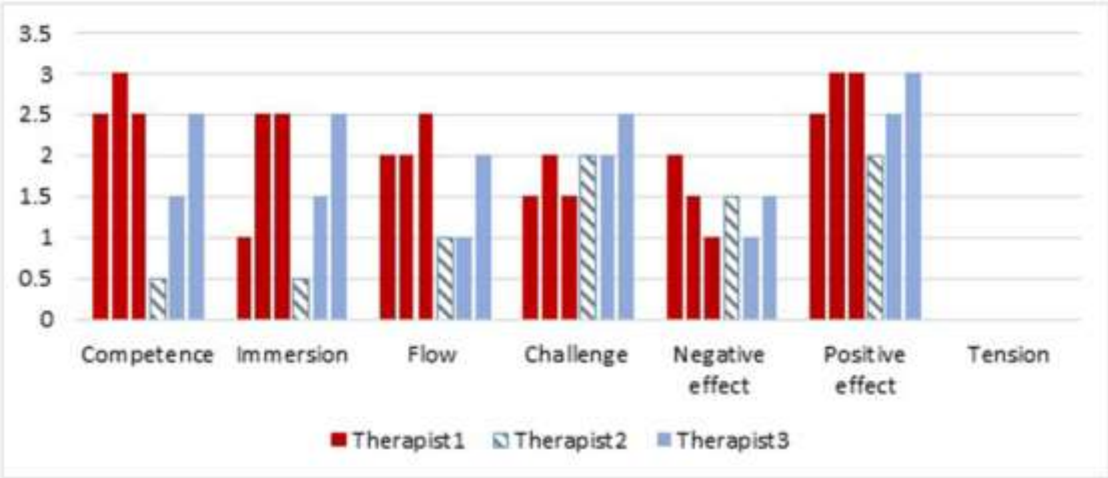


(a)

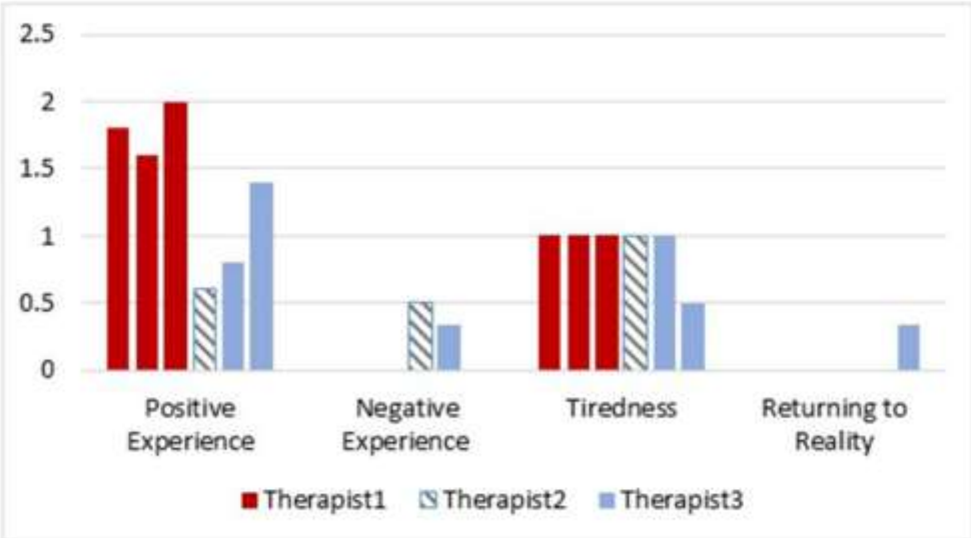


(b)

Figure 5.7 Results of the questionnaires filled in by each patient. (a) In-Game and (b) Post-Game questionnaire. The meaning of the scores on the horizontal axis is reported in Table 4.



(a)



(b)

Figure 5.8 Results of (a) In-Game and (b) Post-Game questionnaires for each patient. On the horizontal axis the category of questions is reported and on the vertical axis the score is specified, according to Table 4. Each bar corresponds to a patient and their different colours indicates the therapist associated to the patient.

During the tests, the performances of the Kinect™ were also evaluated and it was noted that the position of the hands was often arbitrarily inferred by the sensor, resulting into an unnatural behaviour of the avatar hands. Figure 9 shows the percentage of times that the tracked joints were inferred by the Kinect, during a specific session.

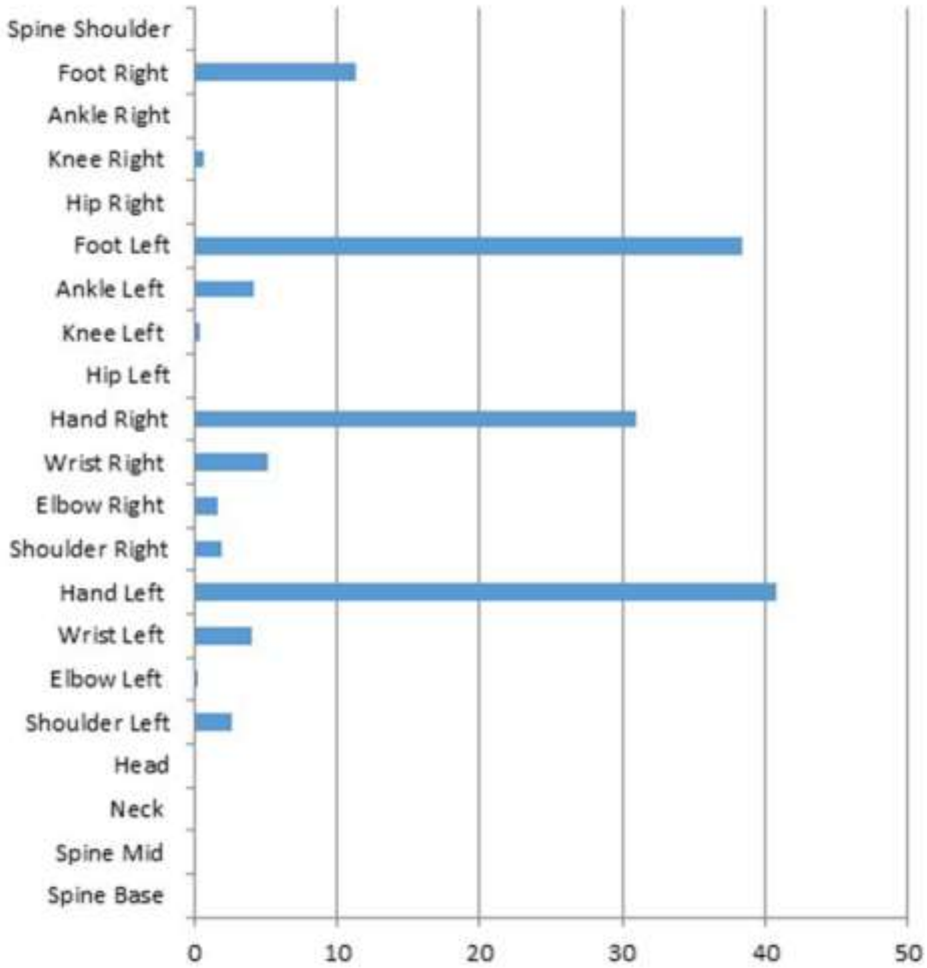


Figure 5.9 Percentage of arbitrary inferences of body joints performed by the KinectTM during a rehabilitation session.

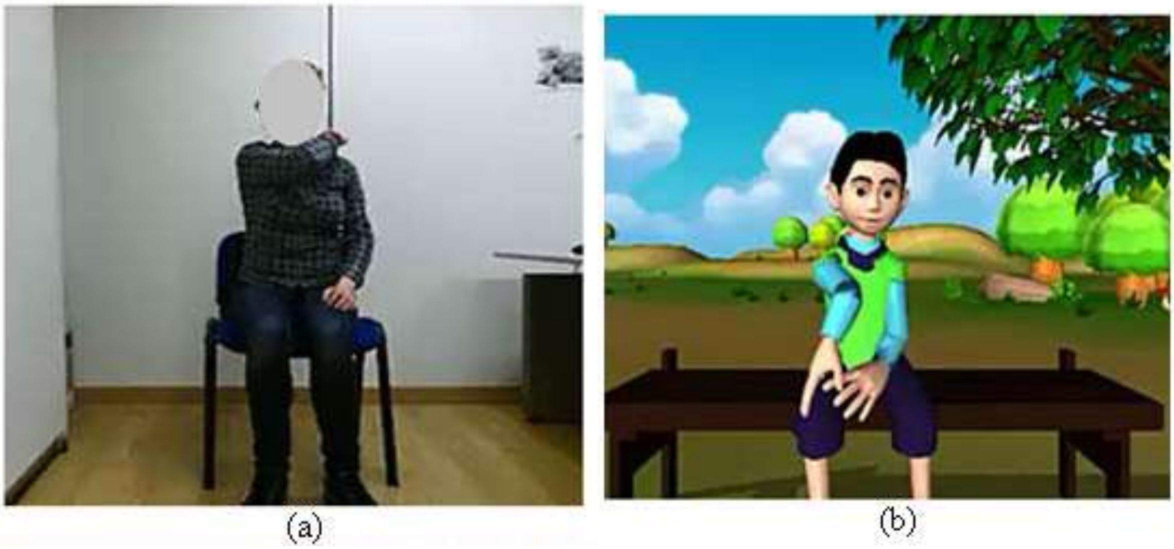


Figure 5.10 Example of an occlusion occurrence. (a) Subject detected by the Kinect™ at the time of occlusion, and (b) corresponding avatar in the virtual environment.

Furthermore, it was noted that the Kinect™ failed to accurately reconstruct the body motion when occlusion issues occurred. Those may happen, for instance, due to the overlapping of the upper limb with the upper body, causing the body tracking to be not reliably, as shown in figure 10.

5.4 Discussion

Nowadays, virtual reality offers interesting opportunities in the rehabilitation field, and is actually largely used. Several studies propose the use of video-games for rehabilitation, and commercially available games have been tested. On the one hand, there are evidences on the necessity to develop video-games for specific group of patients [111], and for this reason, video-games designed for patients affected by specific pathologies have been proposed [103], [107], [109]. They are more like pathology-oriented games, with proper level of automation, and are thus not completely suitable to treat different disorders. On the other hand, there is also a particular attention to patient-oriented approaches where the therapists can design the rehabilitation task driven by their expertise, being supported by virtual reality technology [108], [113], [112]. The design of rehabilitative video-games with the patient-oriented approach, is supported in other studies [125], and automatic methods are also proposed [111]. In this latter case, the automatic development of patient-oriented tasks is performed by specific algorithms, but a long term abilities evaluation is necessary to dynamically adapt. The manual setting by the therapist, adopted in this work, avoids preliminary training of performance detection algorithms, and allows having a system less standardized and more patient-oriented than automatic systems, that can be used with patients affected by different types of pathologies. The proposed software interface reduces the limitations of other systems, allowing the therapist to create new games without complex coding. Traditional rehabilitation practice is then maintained and the therapist has the key-role to define the rehabilitation plan for each patient, according to the specific needs. However, there seems to be still some issues in the easiness of designing patient-oriented video-games by the therapist, as highlighted in [109], where the proposed framework resulted to be difficult to use by one of the therapists.

This study thus proposed a system which was developed in collaborations between engineers and therapists to let the therapist design a patient-oriented rehabilitation task in an easy, user-friendly way, without the need of any specific informatics skills. The system was thus made flexible at source and this allowed a more intuitive usage.

As in Avola et al. [109], the proposed system has the advantage to use a sensor that tracks all the main joints of the human body. This has allowed the development of rehabilitative games involving several parts of the body (e.g. upper limb, lower limb, trunk), avoiding the limitation of other systems, that can be used for a specific rehabilitative application, e.g. [110], [126].

In the case proposed in this study, all the three therapists participating the study could easily design several different tasks, and adapt the level of difficulty of the game to the specific patient. Particular attention was focused on the appreciation of the patients, in order to assess their active participation. The results of the questionnaires filled in by the patients on their overall experience, highlighted the positive aspects of the proposed system and gave the opportunity to identify the future developments. The patient showed interest in the system, as demonstrated by the results of the questionnaires summarized in figure 7. It can be noted that a moderately to fairly positive effect was associated to the In-Game experience. Overall, it is possible to highlight the higher scores associated to the positive feelings of the game (i.e. challenge, flow, immersion and competence) rather than the negative feelings (i.e. negative effect and tension). Among the negative effects, the feeling of tiredness was included as well, but that could be also associated to the motor activity itself, so that it can interpreted as a partially positive effect, from the point of view of the therapy. The above mentioned trend for positive and negative feelings is also maintained in the Post-game questionnaire, as reported in figure 7(b), where the overall positive experience was relatively much evident than the negative ones. The results in terms of tiredness can be interpreted as mentioned above for the In-Game questionnaire.

The results reported in figure 8 show that the therapist acquaintance in using the system was highly related to the satisfaction of the patients. In particular, the three patients assisted by therapist 1, showed more satisfaction, than the two (one) patients assisted by therapist 2 (3). This observation is an evidence on the importance of the interaction between the patient and the therapist [9], [127]. In fact, the more the therapist is confident in using the system, the more the patient is relaxed and positively involved in the rehabilitative activity.

The results illustrated in figure 7 and 8 should be also interpreted by considering the average age of the group of patient, which was 67, and the fact that none of them had previously had any VR experience whatsoever. The definition of further more different scenarios and feedbacks is expected to improve the overall game experience, and overcome the few drawbacks highlighted by the patients.

The choice of adopting the Kinect™ sensor to allow the patient interacting with the virtual environment, guaranteed the control of all the body joints with an acceptable accuracy. The sensor was easy to set up and did not interfere with the rehabilitation task itself. The main limitation was observed in case of occlusions, which may occur during specific exercises when the patients are asked to overlap one of their upper limbs to the upper body. In this case, the Kinect™ sensors is not able to properly track the upper limb joints, whose location is “just guessed” by the software, generating confusion. An example of occlusions was reported in figure 10 and in video 6. In figure 10(a) it is possible to see that the left arm of the subject is overlapping the upper body, and this results into the avatar configuration reported in figure 10(b). Also, hands and feet seemed not to be properly tracked by the Kinect™, for this particular application. As shown in figure 9, those body parts presented a higher probability of not being properly tracked than other parts of the body. In the particular applications presented in this work, a choice was thus taken to keep fixed the position of those extreme parts in the avatar – hands and feet were indeed not important for the success of the rehabilitation sessions. During the planning of a specific rehabilitation exercise, the therapist should thus be aware that, in case occlusions and tracking issues are foreseen, particular care should be taken in order not to generate confusion in the patients, negatively affecting their performance.

Chapter 6.

Conclusions

New technologies, combined with motor learning and motor control theories, are changing Physical therapy and Rehabilitation. Evidences about neuroplasticity, suggest the effectiveness of systems that can promote motor rehabilitation by the application of these concepts [2], [3]. One example is virtual reality, that can be used to create functional stimulus and promote the experience-dependent neuroplasticity.

In this thesis a study of systems for upper limb rehabilitation in post-stroke patients was proposed. The analysis of the state of art, reported in Chapter 1, allowed the identification of the topics that characterize the research activity in this field. This analysis could be divided in two parts: the first one has a clinical orientation; the second one introduces the main technological solutions in upper limb rehabilitation.

The pathology and his effects were briefly introduced in the first part of the introduction. Here the attention was focused on the neurological aspects of the pathology. Stroke causes brain injuries, that lead to disabilities, as the loss of upper limb mobility. Because the nature of this disease, motor control and motor learning methods can be used in conjunction with repetitive trainings [23], [26]. Intensity, frequency and duration of practice are important factors for neuronal reorganization, but it is important to remember that plasticity has an experience-dependent nature [3].

In the second part of the introduction, how neurorehabilitation theories can be supported by technological innovations was showed. In order to facilitate a correct recovery of mobility, the patient has to be induced to execute functional movements, using appropriate stimulus, and, at the same time, the motion has to be monitored and analyzed, to obtain qualitative and quantitative information about performance [23]. At the same time, it is necessary to have affordable, usable and accessible tools, to facilitate their introduction into daily clinical practice [4]. The Kinect for Windows, a depth sensor produced by Microsoft, presents these features. In Chapter 1 how this sensor can be used in the rehabilitation context was introduced. It is a motion control device and, at the same time, it is used to interact with virtual reality. It can be used to track objects and the algorithms to track the human body joints are already integrated in the system. The software associated to this device are open source, and, for this reason, it is largely tested and used in several applications.

Understanding the kinematic of the upper limb, described in Chapter 2, is fundamental for the analysis of the motion. An overview of the motion tracking systems has been proposed. These devices are used to monitor the human body motion and record the variable that characterize the kinematic model of upper limb. Examples are marker-based systems, as the OptiTrack [64], and marker-less systems, as the Kinect for Windows. Marker-based systems guarantee higher accuracy than marker-less devices, but are more expensive, difficult to setup and have to be placed in controlled environments, as a laboratory. Marker-less systems can be advantageous in terms of costs and usability, as in the case of the Kinect sensor.

In this dissertation the usability of the Kinect sensor in upper limb rehabilitation was evaluated, considering two possible applications: for motion classification and as interface with a virtual environment. In fact, it can offer a good compromise between accuracy and usability. This last feature is confirmed by the ease of use and setup. It does not require any calibration and no particular suits or markers are required for the tracking. Furthermore, the body tracking software, developed by Microsoft, allows the tracking of different human body. It does not depend on the high, weight, or on the clothes wear by the person.

On the other hand, the accuracy of the sensor has to be evaluated, in order to understand its limits. Several studies report a comparison between the Kinect sensor and a marker-based system [77], [78], [79], [80], [81] by posture classification, joints center or angles evaluation. Considering the limitations of the existing studies, an analysis of the accuracy of the sensor was conducted. Object and upper-limb tracking were executed and a comparison between a Kinect v2.0 and a marker-based system, the OptiTrack, was reported. In particular, it was investigated the behavior of the sensor when it was placed in different positions and orientations relative to the subject. The results obtained show that the accuracy and precision of the sensor are higher when it is placed in front of the subject. The resolution, of about few tens of millimeters for the experimental test performed here on the upper limb, make the Kinect an interesting tool for applications in the rehabilitation field, including both object and upper limb tracking procedures. It is worth to notice that a more detailed and extensive experimental analysis would be advisable, in order to obtain a more reliable statistical analysis. However, the analysis was useful in confirming that the Kinect performance are somehow dependent on the position and orientation of the sensor.

This observation allowed to understand the results obtained in the development of a classification model, reported in Chapter 4. The study was conducted at the Intelligent Assistive Technology and Systems Lab – IATSL (Toronto Rehabilitation Institute, University of Toronto). In this part of the study the Kinect sensor was used to monitor the posture of subjects during the execution of upper limb exercises using a robot. Five possible postures were considered: *Slouched*, *Raised shoulder*, *Trunk rotation*, *Lean forward*, *No compensation.* The model developed using the data returned by the Kinect v2.0 placed on one side of the subject, indicated as *Model 2*, has an accuracy of 84%, lower than the accuracy of *Model 1,* developed using the Kinect v1.0, placed in front of the subjects.

The lower accuracy reported when the Kinect sensor was not placed in front of the subject justifies the higher number of test samples classified as appertaining to the *Slouched* class by the *Model 2*. In fact, because the bad tracking of the spine_base joint, the trunk orientation showed an higher inclination than the real one, influencing the classification.

It was not implemented a quantitative comparison between the Kinect v1.0 and the Kinect v2.0, but Xu and McGorry, 2015 [80] reported not impressive differences between the two sensors. So, the higher accuracy of the model trained with the Kinect v1.0, can be justified. The accuracy of the classifier is indeed promising and tests with a group of patients has been started at the IATLS, in order to train a new model using these data.

A different application of the Kinect sensor is showed in Chapter 5, where the development and preliminary evaluation of a novel and effective system for the implementation of rehabilitation exercises in a virtual environment is presented. It was developed in collaboration with the Associazione Nazionale Mutilati e Invalidi Civili - Riabilitazione of Crotone (Italy), a qualified rehabilitation center. The main objectives were to investigate (i) whether a flexible system allowing the therapist to design patient-oriented rehabilitative games was a promising tool in rehabilitation, and (ii) whether the Kinect™ sensor could be adopted as a low-cost motion tracking device in this application. Two scenarios have been proposed, where the therapists could define exercises dedicated to the trunk control and the shoulder motion rehabilitation, so upper limb rehabilitation.

The proposed system is feasible and can be of great assistance both to the therapist and the patient. It can be used to record patients' performance, to keep track of their advances and to quantitatively control the execution of each rehabilitative session and exercise. The system was easy to use by the therapists, and the patients resulted to be motivated in performing the rehabilitative exercise, mainly because of the use of the virtual environment, where they were able to interact with virtual objects in more relaxing or stimulating scenarios.

The therapist did not need any informatics knowledge to use the system. This was due to a user-friendly interface, where a set of parameters were easily controlled. The high flexibility of the system was confirmed by the fact that patients were affected by different disorders, none of them encountered difficulties during the tests, and all of them showed interest in the use of the new technologies.

The main limitation of the system is the time consumed by the therapist for the customization of the exercises. The tuning of each parameter require more time than automatic systems, that adapt the games to patients' performances automatically [100].

In the development of the system for the implementation of rehabilitation exercises in a virtual environment, the attention was not only limited to the rehabilitation of upper-limb in post stroke patients. The most important contribution of this system is, in fact, the flexibility and adaptability to different rehabilitative contexts. In this way, the system takes advantage of the full body tracking guaranteed by the Kinect sensor.

In this dissertation different potentialities of the Kinect sensor have been showed. The sensor was used in conjunction with a robot for posture classification and it was also used to interface patients with a customized virtual environment. The two applications are actually separated, but it is obvious that the integration of the two parts of the study is possible, adding the posture classification model in the system for the implementation of rehabilitation exercises in a virtual environment. In order to realize the integration, a training of the classifier using the patients' data is necessary.

Future investigations are expected to give clinical evidences on the effectiveness of the conducted studies. Specific clinical trials should be executed to evaluate the long-term recovery of mobility.

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