Integration of Wearable Inertial Sensors and Mobile Technology for Outpatient Functional Assessment: A Paradigmatic Application to Evaluate Shoulder Stability

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Abstract. Wearable devices based on inertial measurement units (IMUs) are now-a-days a *de facto* standard in the field of human motion analysis. Lower costs, improved quality and enhanced accuracy promote a very fast and diffused adoption of such devices in healthcare and wellness areas. In clinical settings, these technological solutions allow for a quantitative evaluation of functional and clinical tests. This article aimed to present a practical and feasible approach using IMU-based wearable devices and mobile applications to rapidly collect 3D motion information coming from different body segments. The proposed solution was specifically designed for a rapid and precise monitoring of the patient's status both outdoor and indoor, including home and clinical contexts. The modularity concept in designing the application allows to easily plug specific and customized modules addressing data analysis and patient status assessment. The acquired data are always available to the user to be archived or re-processed. Without loss of generality, the developed system was tested in a real clinical context, addressing the need for assessing the shoulder mobility in order to automatically identify the presence of symptomatic or asymptomatic humerus-scapular dyskinesis. This approach allowed to define a kinematic-based set of novels metrics - called Shoulder Primary Key Indicators. The proposed system demonstrated to be a practical and effective solution in the most clinical context, giving room to the adoption of this kind of approach to a wider range of applications related to the functional assessment of different body segments and joints, such as the knee, the spine or the elbow.

Keywords: Healthcare · Mobile apps · Inertial sensors · Motion analysis · Shoulder dyskinesis

1 Introduction

In the last decade, the evolution of inertial measurement units (IMUs) and magneto-inertial measurement units (MIMUs) have been leading to enormous improvements in

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term of precision and hardware quality, with a progressive size and cost reduction. This new wearable technology is slowly spreading around due to several competitive advantages related to other technologies, including lower costs, good quality, easy to setup, waterproof and possibility to be used indoor or outdoor, even in unstructured environment [1–3]. Moreover, inertial and magnetic sensors can be used almost everywhere, thus they can be easily employed in the fields of rehabilitation, wellness and sports [4–6].

The huge success behind this type of "smart" technology is mainly due to their design. A wearable device is basically a tiny computer with sensing, processing, storage and communication capabilities [6]. Improvements in LiPo battery technology, reduced sensor consumption and thanks to the latest Bluetooth Low Energy (BLE) technologies even small devices can provide a long-lasting duration in between two consecutive charge. Wearable inertial devices (WID) can be considered indeed small elaborators integrating a set of Micro-Electro-Mechanical-Systems (MEMS) and magnetic sensors and a wireless communication channel. High performance micro-processors can collect data from sensors up to 1 kHz data rate and directly process on-board data, by applying data-fusion algorithm in order to estimate the device spatial orientation. Processed data and results can be stored locally or can be transmitted in real time over wireless channels.

Developing healthcare application for clinical fields supporting motion-data analysis paradigm requires to face several critical aspects [7, 8]; in particular, when considering outpatient visits, application requirements are mainly related to the context itself, the management of the patients and the overall logistics of the clinical structure. These issues implied the need for portable, low-cost and rapid setup-time applications. This work aimed to report the design, the development and the clinical results of a modular android-based application specifically addressing – but not limited to – the body functional assessment. The system was designed to run on mobile devices and to provide immediate assessment outcomes to the clinicians thus, to complementarily support the clinical assessment. With this work we also aimed to underline the key aspects and critical factors involved in a possible wide adoption of such technology in clinical setting.

2 Materials and Methods

2.1 System Requirements

At design stage, various hypotheses were made in order to obtain a reliable and easy-to-use system. In particular - after having evaluated the use cases in agreement with several opinion leaders - we defined a basic set of functional requirements (FR):

- run on mobile devices (tablet or smartphone) (FR1);
- be easy to use (FR2);
- be easy to acquire data (FR3);
- be easy to setup (FR4);
- provide "general purpose" data analysis (FR5);
- support multiple motion data acquisition devices (FR6);
- provide data storage (FR7).

FR1 means that the application must be able to run on mobile phones and tablets. Mobile phones and tablets are inexpensive and portable devices that can be easily moved around. We initially targeted Android-based devices which are less expensive and more diffused with respect to solutions based on different OS. FR2 and FR3 imply that the application must let the user do not spend much time to manage patient's data and acquisition phase; from the design point of view, specific attention was given to the user interface (GUI), thus to allow the physicians to quickly go through data entry and data acquisition. FR4 stands for the ability to easily and rapidly positioning and calibrating of wearable sensors; subject calibration must not take more than few seconds, indeed. FR5 allows to use the system for different types of acquisition, including – for instance - gait analysis, shoulder assessment, upper and lower limb functional testing, etc. The possibility to support multiple device vendors (FR6) allows to support both low-quality inexpensive devices such as high-quality expensive devices depending on the economic availability. Finally, FR7 provides the ability to store acquired motion data in local database or in XML files. Stored data can be used for a deeper analysis if required; cloud storage was also envisaged.

Furthermore, application's modularity represents a key aspect of the overall project. In general, approaching human motion analysis, setup and data acquisition are common phases in all the considered possible use cases. Usually, common phases (CP) include: (CP1) subject identification, (CP2) setup, (CP3) calibration, (CP4) data acquisition. Data analysis is indeed specific for each type of acquisition; therefore, data processing and visualization specifically require a "plug-and-play" approach. Thence, the application was designed to have a generic core architecture which can be used in various type of data acquisition applications, whereas several modules were thought to be customized in order to interface to specific device vendor, to provide dedicated data processing and to provide detailed representation of the clinical outcomes.

2.2 Hardware Selection

Following FR1, the application was designed to run on any Android device that support at least Android Oreo (i.e. 8.0), which corresponds to API level 26. For the validation of the system, the developed application was tested on the Motorola One mobile phone.

The selection of the WID vendor for clinical trials implied the definition of specific requirements, since on the market there are several different manufacturers, each one providing a product with its own advantages and disadvantages. Basic requirements were identified as:

- Low-cost;
- In a minimal set of 3 devices;
- Bluetooth communication;
- Rechargeable;
- 9DoF sensors data.

Browsing the market, the following available products were found and evaluated: DOT by Xsens [9] and Wearnotch by Notch Interfaces [10]. Other systems were excluded due to costs, number of devices or need for dedicated base station.

Between DOT and Wearnotch, we finally decided for the second one for the following reasons:

– Support for Android devices (a very complete SDK is provided);
– Software already available with clear practical examples;
– Set of 6 devices;
– Practical case;
– Waterproof;
– Easy to calibrate.

Among several features provided by the Notch SDK, there are a couple of interest: 1) an already available calibration process with respect a base subject position and 2) a graphical representation of the subject activity, that can be used to show – even in real time – the body posture and movements. Moreover, the subject's base-position (also called "steady position") for initial calibration can be easily personalized. Finally notch devices have a multi-color led that can be used to identify each single device thus, to support an easy positioning of the sensors on the correct body segment.

2.3 Software Design and Development

The mobile application was developed using Android Studio®, exploiting the SDK provided by Notch Interfaces.

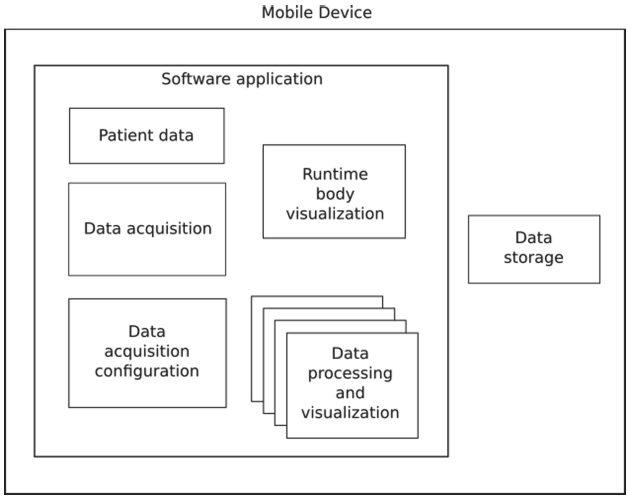


Fig. 1. Modular representation of the mobile software application.

Considering the modular structure of the application (Fig. 1), we identified 7 main modules, including:

- Patient Data Service (PD);
- Data Acquisition (DA);
- Data Acquisition Configuration (DAC);
- Runtime Body Visualization (RBV);
- Data Processing and Visualization (DPV);
- Data Storage (DS);
- Communication Bus (CB).

The PD, DA, DAC and RMV modules are part of the core application; this implies that, regardless of any body segments you aim to analyze and any assessment you want to perform, this set of modules and their interaction never change.

The DPV module may change depending by the specific application or functional analysis; this module must be designed to processes the acquired data in order to infer the results and represent the data, considering their clinical meaning and importance.

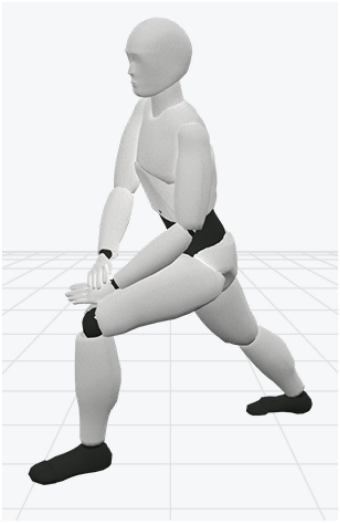
PD module takes care of the management of the patient's data and information. Connects directly to the persistence service to retrieve already profiled patients. Moreover, to speed up the process the physician can proceed with data acquisition without validating the patient's data.

DA module allows for data acquisition, connecting with the hardware devices interface. This interface provides a generic callback-based interface framework to abstract the physical hardware and to provide transparences with respect the specific hardware vendor solution. All the information related to each acquisition session are saved as XML files or entered in a dedicated database. DAM is supported by the DAC module which has been conceived to manage the device configuration. This means that DAC component must perform two tasks: 1) define the number of sensors to use and 2) define the position of each device on the body segments. This information is controlled by a json-formatted configuration file (Fig. 2(b)).

The RBV module was conceived to receive data from DAM and to apply them to the skeleton to provide a real-time feedback of the movement to the user. Real-time feedback is important in order to check both the running status of the system, the sensors configuration and the avatar calibration. During runtime body visualization, the user can ask the patient to perform some preliminary simple movements in order to verify the correctness of the setup. If calibration is wrong or the device configuration is not the right one, the user can go back and fix any possible issue.

Figure 2(a) reported an example of the standard avatar given by Notch Interfaces, in a specific pose. After the opportune calibration, data acquired by the WIDs are directly applied to the avatar's body segment to reflect subject's position.

The DPV module processes acquired motion data in order to perform the user's data analysis. Processed data are then shown to the user adopting specific visualization depending on the analysis performed. For sake of clarity, in the next sections we present the "Shoulder Stability Assessment" module (SSAM). The SSAM basically uses two WIDs, one applied to the humerus and one to the scapula in order to identify dyskinesis in the scapulo-humeral rhythm.



(a)


```
{
    "bones": [
        {
            "name": "LeftCollar",
            "color1": "Red",
            "color2": "Red",
            "frequency": 20
        },
        {
            "name": "LeftUpperArm",
            "color1": "Green",
            "color2": "Green",
            "frequency": 20
        },
        {
            "name": "LeftForeArm",
            "color1": "Blue",
            "color2": "Blue",
            "frequency": 20
        }
    ],
    "master_bone": "LeftUpperArm",
    "special": {
        "bone": "LeftUpperArm",
        "orientation": "Left"
    }
}
```


(b)

Fig. 2. (a) Example of avatar graphical representation (image published on Wearnotch's website at https://wearnotch.com/). (b) Example of the configuration file for the Data Acquisition Configuration (DAC) module.

The DS module was designed to handle the access to the database providing transparent access to various persistence solutions: SQLite and Cloud to cite two of them. Cloud based persistence allows the storage of the data in the cloud where can be accessed from other applications to outperform further and more detailed analyses.

Finally, all the modules relate to an event driven communication bus used, for example, by the data acquisition module to share the acquired data among other modules such as the DMV. The CB is basically an event bus with the subscriber-dispatcher paradigm. Whenever an event is dispatched all the registered listener gets automatically notified. The CB allows for a transparent pluggable mechanism for the custom modules DPV to receive notification of events or the motion data in real-time without a direct interface binding easing module integration.

2.4 "Shoulder Stability Assessment" Application: Development and Validation

Without loss of generality, we declined the system into a specific application to assess the shoulder stability, we called the "Shoulder Stability Assessment" (SSA) application. This app included a specific DPV module able to display all the information concerning the clinical assessment.

Application Modules

The application presents an initial GUI, where the user can set the patient's information (Fig. 3 Left), a main interface with the possibility to connect the sensors and calibrate the avatar (Fig. 3 Center), and a runtime visualization and acquisition interface, which

allow the view in real-time the movement performed by the patient, mapped on the avatar (Fig. 3 Right).

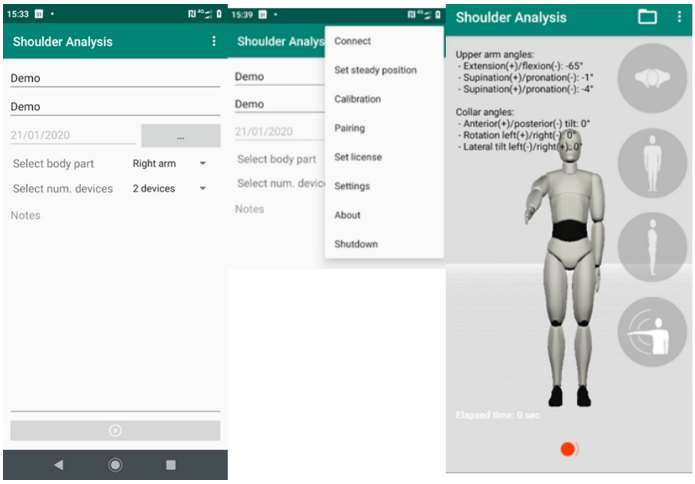


Fig. 3. App initial interface (left), main interface (center) and runtime visualization interface (right).

The mobile application was tested on-field with a dedicate DPV module to assess the shoulder stability in order to discover presence of dyskinesis in the scapula-humeral joint. The DPV module, for this specific use case, was addressed to the possibility to identify asymptomatic shoulder dyskinesis by using a set of shoulder primary key indicators (SPKIs), as hereinafter reported. The role of the system was to extract these specific SPKIs from the motion data acquired during the execution of defined tasks and report them to the user to support clinical decision.

The Shoulder

The shoulder articular complex is made of synovial articulations and functional articulations [11]. This means the shoulder is a complex structure characterized by wide mobility at the expense of overall instability. The shoulder consists of four distinct articulations: the glenohumeral joint, the chromium clavicular joint, the sternoclavicular joint, and the scapulothoracic articulation [12]. These biomechanics characteristics gives to the shoulder articular complex a huge sensibility to a various pathological dis-order: acute disorders (such as subluxations, dislocations, instability, bunions etc.) and chronic disorders (such as tendinitis-tendinosis, broken tendons due to over-load or over-work). Lesions of soft tissue of the shoulder are seconds only to the vertebral spine lesions in term of disability costs [13].

The application has been tested to acquire shoulder data in the initial phase of the abduction movement. Given the shoulder biomechanical characteristic [14–18], we consider the micro-modification of the scapulo-humeral joint dynamics, in the initial abduction movement, significative in the identification of the presence of shoulder kinesis and impingements. The shoulder dynamic in the initial phase of the movement has been describe a set of SPKIs.

Subject Selection and Group Definition

In order to validate the system, a preliminary pilot study was performed on voluntary subjects. Each subject was asked to report the presence of any pathology at the shoulder level, including (1) tendinitis-tendinosis of the rotator cuff, (2) tenosynovitis of the biceps caput longum, (3) subacromion-deltoidea bursitis, (4) partial or total lesion of the rotator cuff, (5) frozen shoulder and (6) articular movement limitation associated or not with muscle hypostemia. All the subjects were previously informed on the main aim of the study and they gave to the experimenter their open consent. The following groups were identified:

1. **Group HF (GHF)** included all the female subjects with no shoulder pathology.
2. **Group PF (GPF)** included all the female subjects with any reported shoulder pathologies,
3. **Group HM (GHM)** contains all the male subjects with no shoulder pathologies and normal shoulder functionalities.
4. **Group D (GDP)** contains all the male subject with shoulder pathologies.

Validation Setup

All the data were acquired on the subject standardizing the setup. Specifically, the subject was seated on a stool, with standing vertebral column and both arms laying down along the side of the body. The height of the stool was set in order to have a proximal 90° angle on the knee. With the subject in this position, three WIDs were specifically positioned on the acromion, the humerus and the radio, as reported in Fig. 4 (left). For all the sessions, all the WIDs were placed by the same person, who was previously trained in this operation. The device on the scapula was placed on the postero-lateral side of the acromion, whereas the device on the humerus was positioned on the distal lateral side. The device on the radio was used to check the configuration, communication and real-time features. In this work, we did not take into consideration the thorax movements of the subject while executing the required task, since we empirically verified that the thorax compensation was almost negligible.

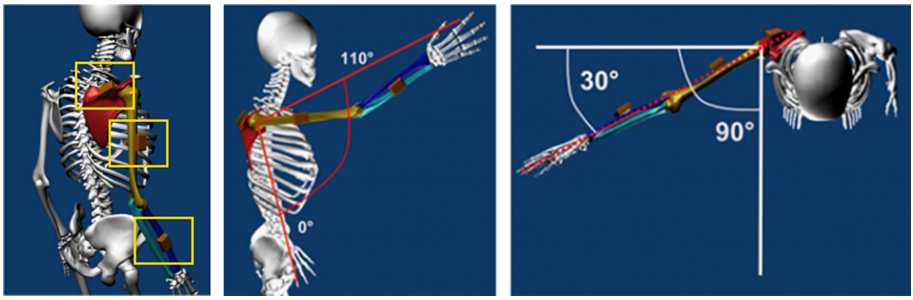


Fig. 4. WDIs positioning on the scapula and upper limb (left) and required movement in the sagittal (center) and coronal (right) planes.

The steady calibration was performed with the targeted arm relaxed; lying on his side. Overall calibration takes no more than 2/3 s. Then, each subject was specifically asked to execute an abduction movement of the upper limb (ULA) starting from the steady position up, rising the upper limb and maintaining it within the scapular plane, with a normal speed, up to reach the maximum abduction level without feeling pain, and back (Fig. 4, center and right). Before recording the data, the subject was asked to simulate the movement thus, to verify the task and train for the exercise. In order to test the reliability of the approach, the subject was required to execute a minimum of three to a maximum of five movements. Between each ULA, a pause of 5 s was applied to not induce muscular fatigue. The rhythm of the movement execution was manually driven by an external trigger. Motion data acquired by the WIDs were used to compute the following planar angle rotations:

– Scapula frontal plane rotation (SFPR);
– Scapula sagittal plane rotation (SSPR);
– Humerus abduction (HA);
– Humerus axial rotation (HR);
– Humerus extra-rotation (HE).

In the definition of these SKPIs, we kept into account the functional relationship that is present among different rotation angles (e.g. between HA and SFPR and between HA and HR). Each SPKI was extracted from the angular values, by performing several hypotheses on their progress in time. Considering the graphs reported in Fig. 5, we can define the following parameters:

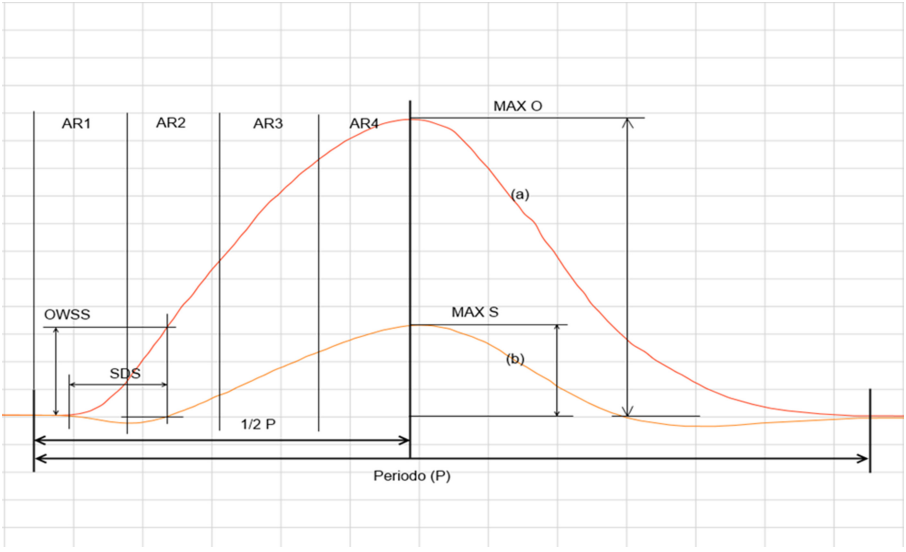


Fig. 5. Details of HR (red line) and SFPR (yellow line) angle during a single upper limb abduction (ULA). (Color figure online)

- **P** as the overall period of a single ULA;
- **P′** is the instant of the period P, when the humerus reaches the maximum abduction value;
- **MAXS** is the maximum scapular rotation on the frontal plane;
- **MAXO** is the maximum humerus abduction value;
- "Scapula delta start segment" (**SDSs**), as the segment identified by the initial abduction movement to the moment in which the scapular rotation crosses the zero line (which is considered the steady position of the humerus);
- "Humerus when scapula starts" (**OWSS**), is the value of abduction (in degrees) of the humerus when scapula starts, so when scapula cross the zero axis.
- "Humerus when scapula is 5°" (**OWSS5**) is the value of abduction (in degrees) of the humerus when scapula rotation reaches 5°.
- "Area ratios" (**AR1p**, **AR2p**, **AR3p** and **AR4p)** are 4 areas obtained dividing the whole P′ range in 4 equal parts; in this analysis only AR1p was considered.

From all these parameters, several SPKIs were identified, including:

- **OWSS** and **OWSS5** identified the humerus abduction when scapula start moving and when scapula reaches the 5° of rotation respectively.
- **SDS** defined as reported in Eq. (1):

$$\mathrm{SDS} = (\mathrm{SDSs}/\mathrm{P}) * 100 \tag{1}$$

- **AR1** defined starting from the corresponded AR1p value, applying the Eq. (2):

$$\mathrm{AR1} = (\mathrm{AR1_S}/\mathrm{AR1_O}) * 100 \tag{2}$$

where: $\mathrm{AR1_S}$ is the area of the scapula time series in zone AR1;
$\mathrm{AR1_O}$ is the area of the humerus time series in zone AR1.

- **MOAR** defined as the maximum humerus axial rotation normalized with respect the main humerus abduction value considering graphs reported in Fig. 6 and using the Eq. (3):

$$\mathrm{MOAR} = (\mathrm{M2}/\mathrm{M1}) * 100 \tag{3}$$

where: M1 is the maximum humerus abduction value;
M2 is the maximum humerus axial rotation.

All SPKIs were computed for each ULA movement and a mean value was evaluated considering all the ULA movements acquired by the system. In order to clearly report the data to the final user, we decided to introduce a discretization of the values obtained for each SPKIs by introducing a score with 4 grades:

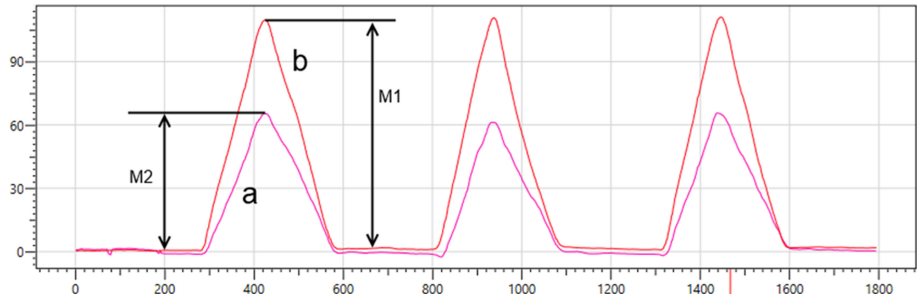


Fig. 6. Humerus abduction (b) vs. humerus main-axis rotation (a) during three ULA movement.

– S1: when the SPKI is in the range [0–6);
– S2: when the SPKI is in the range [6–11);
– S3: when the SPKI is in the range [11–16);
– S4: when the SPKI is $\geq$16

These grades consider the distribution of the SPKIs, obtained during the acquisition sessions. Furthermore, we verified the reliability of the system in the clinical context by qualitatively analyzing its inherent usability through unstructured interview performed involving two opinion leaders.

3 Results

This work presented a twofold aim. The first objective was to experiment the possibility to adopt inertial sensors and mobile applications in clinical settings, in order to acquire motion data on subject, thus, to assess his/her functional state. The second objective was to try to apply the developed system in a paradigmatic context and therefore verify the possibility to assess the presence scapula-humeral dyskinesis. Hereinafter, the main results obtained and related to both the aims are presented and discussed.

3.1 Wearable Inertial Devices and Mobile Application

The first objective was verified by evaluating the overall usability of the system. We provided the system – consisting in a mobile phone and WIDs - to two clinicians, who performed some test on voluntary subjects. A training was executed with all the clinicians involved in the experimentation. During the training we showed the clinicians how to apply the sensors and how to use the mobile application to acquire data and save them. With the experts, we also designed the overall protocol to use to acquire the motion data. Further, clinicians were followed during the use of the system in order to provide support if needed and to verify how they were able to handle the overall solution.

The results obtained for this aspect of the work, were very interesting. The clinicians involved in the experiment resulted to be very comfortable with the adoption of this technology. Mobile phones are indeed very diffuse in their environment and they were very keen in using the phone normally during their daily work (e.g. to communicate

with their patients and coworkers). They were very pleased of the provided commodity and of the possibility to have the entire system "in pockets of their medical gown". No difficulties nor critical events where encountered during WID positioning or system use. Further analysis will include the possibility to perform a pilot study quantitatively addressing the usability of the system, by introducing proper scores and questionnaires.

3.2 Humerus-Scapular Dyskinesis Assessment

The second objective of this work was to verify the possibility to identify symptomatic or asymptomatic humerus-scapular dyskinesis by exploiting motion information acquired by using two WIDs and a dedicated module for the analysis.

In particular, the validation included 82 subjects of age ranging between 19 and 80 years. Demography and pathology presence are reported in Table 1.

Table 1. Demography data.

Subjects	Pathological	Non-pathological
45 females	18	27
37 males	15	22

This section presents the final SPKIs analysis, performed on a total of 52 subjects. Without loss of generality, in this discussion we reported the results obtained on OWSS, SDS and AR1 parameters. In order to limit any possible difference due to gender characteristics, we divided the analysis considering separately males and females. In Table 2 we report SPKIs for female subjects, considering those who reported a joint pathology and those who did not.

In the same way, Table 3 shows the characteristic SPKIs data for male subjects grouped into "Pathology" and "NO-Pathology".

Focusing on females, OWSS, SDS and AR1 well demonstrated to be the extremely significant indicators in the identification of specific pathology of the scapulo-humeral joint. Considering OWSS, more than 81% of non-pathologic female subjects reported an index value OWSS larger than 16. On the other hand, 100% of the pathologic female subjects presented an OWSS value lower than 16. Furthermore, SDS well discriminated for the presence of pathology, where 100% of the female subjects presented a value lower than 11. In this case, SDS was not so significant in identifying non-pathological subjects. In this group around 63% of the subjects presented an SDS value lower than 11 and 37% of the subjects remain in the range S2. In this case, the identified thresholds resulted to be not the optimal selection. We discuss this point hereinafter, in the Discussion. Eventually, also AR1 index was quite a good indicator for the identification of the presence of a dyskinesis in the humerus-scapular joint. With this SPKI 100% of the female subjects in PFG presented a value above 6 and only 11% reported an index below 11. Among the "No-Pathology" subjects, 70% presented a value of AR1 below 11. Similar evidences are present in the male groups; focus - for instance - on OWSS index.

Table 2. Characteristic SPKIs for female subjects divided into "NO-Pathology" and "Pathology" groups.

Data	NO-Pathology	Pathology
Quantity	27	18
Age		
MIN	30	25
MAX	86	80
MEAN	56	59
OWSS		
From [0–6)	0	1
From [6–11)	0	11
From [11–16)	5	6
Above 16	22	0
SDS		
From [0–6)	0	7
From [6–11)	10	11
From [11–16)	14	0
Above 16	3	0
AR1		
From [0–6)	13	0
From [6–11)	6	2
From [11–16)	5	5
Above 16	3	11

Table 3. Characteristic PKIs for male subjects divided into "NO-Pathology" and "Pathology" groups.

Data	NO-Pathology	Pathology
Quantity	22	15
Age		
MIN	19	44
MAX	72	77
MEAN	46	62

(*continued*)

Table 3. (*continued*)

Data	NO-Pathology	Pathology
OWSS		
From [0–6)	0	0
From [6–11)	0	9
From [11–16)	2	2
Above 16	20	4
SDS		
From [0–6)	0	5
From [6–11)	2	8
From [11–16)	8	2
Above 16	12	0
AR1		
From [0–6)	12	1
From [6–11)	7	1
From [11–16)	1	5
Above 16	2	8

4 Discussion

This preliminary work is mainly focused on the design and development of a system integrating a mobile application and WIDs addressing the clinical field. From the usability point of view, we demonstrated that these tools were very appreciated by the clinicians and that functional assessment in real-time is possible. In our experimentation we sought to keep all things as simple as possible. In this context, we must investigate what could happen if the number of WID increase and the WID setup get more complex. In this case, the adoption of the presented solution will not be immediate, since the scalability of the technology should be well evaluated for each specific application. However, one of the points where application engineering must put attention is the possibility to optimize the number of WIDs to use for a given analysis, keeping it as low as possible. From the use case analysis, the subject preparation must be comfortable and rapid, movement to execute must be easy and short to complete. The key points, which worth for the clinicians - after the patient's health-, are time, simplicity and result. Applications which provide short set-up time, easy movement execution and provide reliable results would have a good spread in the clinical environment.

The second objective of this work was to apply the developed solution to the assessment of humerus-scapular dyskinesis. The target of this work was only to verify the possibility to functionally asses the joint by using the 3D motion data acquired by using the developed system. In our work we analyzed the shoulder behavior in the very

first dynamic of humerus abduction executed on scapular plane, were we specifically defined several SPKIs to characterize the shoulder status. Many works were dedicated to the shoulder assessment [19–22] but none of them concentrate research in the specific initial phase of the shoulder movement as key aspect in dyskinesis identification. As explained in [23], in a non-pathological subject, the scapula start moving when the humerus reaches the 30° of abduction on scapular plane. Always in [23] they high-lighted the fact that the kinematics of the humerus-scapular joint in the first 30° of humerus abduction is very difficult to measure and that the same kinematic behavior is very difficult to standardize. This means that the kinematic behavior of the humerus-scapular joint in the initial motion is very subjective and that would change from subject to subject. On the contrary, the humerus-scapular joint, when humerus abduction is over the 30°, manifests common behavior among all subjects with a constant ratio of around 1-to-2 between the rotation of humerus and scapula [23]. The basic idea is to characterize a similar behavior by using a wide set of SPKIs in order to better address the investigated kinematics. In non-pathological subjects we specifically expected that OWSS and OWSS5 was like those reported in [23] (scapula start moving when the humerus reached the 30° of abduction on scapular plane). On the other hand, in pathological subject we expected that the scapula started mowing just before the humerus reaches 30° of abduction. Moreover, we expect that the humerus-scapular joint kinematics, de-spite the high variability among non-pathological subjects, showed characteristic patterns among pathological subjects. In this work, we marginally considered the behavior of the humerus-scapular joint when the humerus abduction reached values above 30° of abduction. This choice is since, above this value, the kinematic patterns are quite simple, with a maximum static value which identify the overall range of motion. Besides the humerus abduction value with respect to the scapular rotation, this work took also into consideration the relationship between humerus abduction value and the humerus axial rotation. Also, in this case we expected a wide and variable kinematic pattern for non-pathological subjects and a characteristic behavior for pathological subjects, thus giving us the possibility of introducing similar and classifiable behavioral patterns. The problematic relative to the Intraclass Correlation Coefficients (ICC) [24–29] has not been considered in this work and will be subject of future investigation. Herein, to reduce the ICC effects on measured data all the WID setup has been performed by the same person. The results obtained are interesting and demonstrated the feasibility of the proposed solution. From the data discussed in previous sections, these results were somehow unexpected. When we started this work, we were not sure that SPKIs would be able to classify pathological subjects. The asymmetric patterns defined by the SPKIs between pathological and non-pathological sub-jects are extremely evident in the acquired data.

In order to automatically identify the presence of the pathology, by considering at the same time several SPKIs, we are strongly working on the possibility to introduce AI solutions. We recently performed a first and preliminary test using a basic Perceptron based Neural Network (NN) with 5 inputs and a single output (pathologic or non-pathologic subject). The results were extremely promising. Using half of the samples for NN training and half of the sample for the test, we obtained a correct classification score of 90% which means one single error on a set of 22 subjects processed.

5 Conclusion

The presented work highlighted how a rapid, comfortable and easy-to-use system can be used in the most clinical setting. The integration of inertial sensors and dedicated mobile app were able to provide reliable information related to the functional assessment of a joint. A paradigmatic application was indeed realized considering the possibility to assess the humerus-scapular joint kinematics and allowing for dyskinesis identification in both symptomatic and asymptomatic cases. The provided system allowed us to design a set of specific kinematic-based parameters, which were extremely discriminative in identifying the presence of any joint pathology. This approach can be easily generalized to further applications and assessments. Future developments will mandatorily focus on the necessity of introducing automatic classification solutions.

References

1. Roetenberg, D.: Inertial and magnetic sensing of human motion [s.n.], S.l. (2006)
2. Krüger, A., Edelmann-Nusser, J.: Application of a full body inertial measurement system in alpine skiing: a comparison with an optical video based system. J. Appl. Biomech. **26**(4), 516–521 (2010). https://doi.org/10.1123/jab.26.4.516
3. Deppe, O., Dorner, G., König, S., Martin, T., Voigt, S., Zimmermann, S.: MEMS and FOG technologies for tactical and navigation grade inertial sensors-recent improvements and comparison. Sensors **17**(3) (2017). https://doi.org/10.3390/s17030567
4. Avci, A., Bosch, S., Marin Perianu, M., Marin Perianu, R., Havinga, P.J.M.: Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: a survey, pp. 167–176, February 2010
5. Patel, S., Park, H., Bonato, P., Chan, L., Rodgers, M.: A review of wearable sensors and systems with application in rehabilitation. BioMed. Cent. (2012). https://doi.org/10.1186/1743-0003-9-21
6. Sazonov, E., Neuman, M.R. (eds.): Wearable Sensors: Fundamentals, Implementation and Applications. Academic Press is an imprint of Elsevier, Amsterdam (2014)
7. Leonard, K.: Critical success factors relating to healthcare's adoption of new technology: a guide to increasing the likelihood of successful implementation. Electron. Healthc. **2**(4), 72–81 (2004)
8. Ventola, C.L.: Mobile devices and apps for health care professionals: uses and benefits. P T Peer-Rev. J. Formul. Manag. **39**(5), 356–364 (2014)
9. XSENSE DOT, 07 February 2020. https://www.xsens.com/xsens-dot
10. Wearnotch, 07 February 2020. https://wearnotch.com
11. Bencardino, J.T. (ed.): The Shoulder: Imaging Diagnosis with Clinical Implications. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-06240-8
12. Bronzino, J.D., Peterson, D.R.: Biomedical Engineering Fundamentals. CRC Press (2017)
13. Rockwood, C.A.: The shoulder. Saunders/Elsevier, Philadelphia (2009)
14. Ludewig, P.M., Braman, J.P.: Shoulder impingement: biomechanical considerations in rehabilitation. Man. Ther. **16**(1), 33–39 (2011). https://doi.org/10.1016/j.math.2010.08.004
15. Watson, L., Balster, S.M., Finch, C., Dalziel, R.: Measurement of scapula upward rotation: a reliable clinical procedure. Br. J. Sports Med. **39**(9), 599–603 (2005). https://doi.org/10.1136/bjsm.2004.013243
16. McCluskey, G.M., Getz, B.A.: Pathophysiology of anterior shoulder instability. J. Athl. Train. **35**(3), 268–272 (2000)

17. Tate, A.R., McClure, P., Kareha, S., Irwin, D., Barbe, M.F.: A clinical method for identifying scapular dyskinesis, part 2: validity. J. Athl. Train. **44**(2), 165–173 (2009). https://doi.org/10.4085/1062-6050-44.2.165
18. McClure, P., Tate, A.R., Kareha, S., Irwin, D., Zlupko, E.: A clinical method for identifying scapular dyskinesis, part 1: reliability. J. Athl. Train. **44**(2), 160–164 (2009). https://doi.org/10.4085/1062-6050-44.2.160
19. Garofalo, P.: Development of Motion Analysis Protocols Based on Inertial Sensors Healthcare Applications. Lambert Academic Publishing, Saarbrücken (2011)
20. Körver, R.J.P., Senden, R., Heyligers, I.C., Grimm, B.: Objective outcome evaluation using inertial sensors in subacromial impingement syndrome: a five-year follow-up study. Physiol. Measur. **35**(4), 677–686 (2014). https://doi.org/10.1088/0967-3334/35/4/677
21. Hsu, Y.-L., et al.: A wearable inertial-sensing-based body sensor network for shoulder range of motion assessment. In: 2013 1st International Conference on Orange Technologies (ICOT), Tainan, pp. 328–331, March 2013. https://doi.org/10.1109/ICOT.2013.6521225
22. van den Noort, J.C., Wiertsema, S.H., Hekman, K.M.C., Schönhuth, C.P., Dekker, J., Harlaar, J.: Measurement of scapular dyskinesis using wireless inertial and magnetic sensors: importance of scapula calibration. J. Biomech. **48**(12), 3460–3468 (2015). https://doi.org/10.1016/j.jbiomech.2015.05.036
23. Inman, V.T., Saunders, J.B., Abbott, L.C.: Observations of the function of the shoulder joint. Clin. Orthop. (330), 3–12 (1996). https://doi.org/10.1097/00003086-199609000-00002
24. Koo, T.K., Li, M.Y.: A guideline of selecting and reporting intraclass correlation coefficients for reliability research. J. Chiropr. Med. **15**(2), 155–163 (2016). https://doi.org/10.1016/j.jcm.2016.02.012
25. Gallin, J.I., Ognibene, F.P., Johnson, L.L. (eds.): Principles and Practice of Clinical Research, 4th edn. Academic Press, London (2018)
26. Liu, L.: Biostatistical basis of inference in heart failure study. In: Heart Failure: Epidemiology and Research Methods, pp. 43–82. Elsevier (2018)
27. Riffenburgh, R.H.: Statistics in Medicine, 3rd edn. Elsevier/AP, Amsterdam (2012)
28. Hoffman, J.I.E.: Biostatistics for Medical and Biomedical Practitioners. Academic Press, Amsterdam (2015)
29. Laboratory statistics. Elsevier, Waltham (2017)