Leveraging IMU Data for Accurate Exercise Performance Classification and Musculoskeletal Injury Risk Screening

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Abstract— **Inertial measurement units (IMUs) are becoming increasingly prevalent as a method for low cost and portable biomechanical analysis. However, to date they have not tended to be accepted into routine clinical practice. This is often due to the disconnect between translating the data collected by the sensors into meaningful and actionable information for end users. This paper outlines the work completed by our group in attempting to achieve this. We discuss the conceptual framework involved in our work, the methodological approach taken in analysing sensor signals and discuss possible application models. The work completed by our group indicates that IMU based systems have the potential to bridge the gap between laboratory and clinical movement analysis. Future work will focus on collecting a diverse range of movement data and using more sophisticated data analysis techniques to refine systems.**

I. INTRODUCTION

Effective implementation of exercise therapy and accurate measurement of injury risk screening tools are critical elements for performance enhancement and injury prevention in healthcare and sport. However, there are barriers to successful implementation of both. For exercise implementation, practitioners and strength and conditioning (S&C) coaches are faced with a myriad of issues associated with poor adherence and the inability to maintain good exercise technique. This can result in ineffective training and rehabilitation in addition to increasing the risk of injury [1]. When assessing for injury risk, practitioners have traditionally relied on visual observation and subjective evaluation using tools such as the Functional Movement Screen (FMS) [2] and other lower extremity screening tests [3]. This approach relies heavily on the observer's clinical expertise and is associated with only moderate intra-rater and inter-rater reliability [4]. More objective quantification of injury risk can be ascertained via detailed laboratory analysis. However this option is only available to a very small sector.

Recent technological advances have allowed for the development of equipment that supports practitioners in addressing these challenges. A wide range of wearable sensor technologies is now available, allowing for objective movement analysis in a clinical or home environment. Inertial measurement units (IMUs) have been developed to provide interactive feedback and compliance monitoring to people carrying out exercise therapy. These are usually based on tracking movement during exercise and using the movement metrics as input for audio-visual feedback.

However, these technologies have not been widely accepted into routine practice in clinical or S&C settings. One of the critical limiting factors is the disconnect between the capability of these systems to measure movement and being able to provide actionable information to the various stakeholders involved in their application. Being able to accurately track movement using an IMU does not help the clinician easily recognize where their client has deviated from normal biomechanical form without appropriate signal processing and actuation strategies.

In this paper we describe a data driven model that aims to address these issues. We discuss the conceptual framework involved in using IMUs to provide meaningful data to end users (section II), the methodological approach being implemented to achieve this (section III) and finally discuss practical applications of such systems (section IV).

II. CONCEPTUAL FRAMEWORK

A framework must be put in place in order to effectively transform sensor data into useful information for the relevant stakeholders (clinicians, sports scientists, athletes, patients, etc.). The steps involved in this are outlined in Figure 1. The first step is to create a context specific evaluation framework. With both exercise performance evaluation and injury risk screening it is necessary to identify correct form and common deviations from the same according to an agreed clinical consensus. This clinical consensus may be obtained through the use of previously validated frameworks [3, 5]. This was the approach taken in our work where possible [1, 6]. Where these published guidelines do not exist, it may be necessary to formulate new guidelines through the use of clinician-orientated questionnaires. Once this framework has been identified it is necessary to expose the sensors to the specific movement characteristics that are associated with correct and incorrect performance.

The next step is to develop a data query model that adheres to the evaluation framework, and an associated actuation strategy. The system needs to be able to identify the exercise completed, segment the repetitions of the exercise, extract features from each repetition signal and classify the

*Research supported by the Irish Research Council (EPSPG/2013/574) and Science foundation Ireland (12/RC/2289). .

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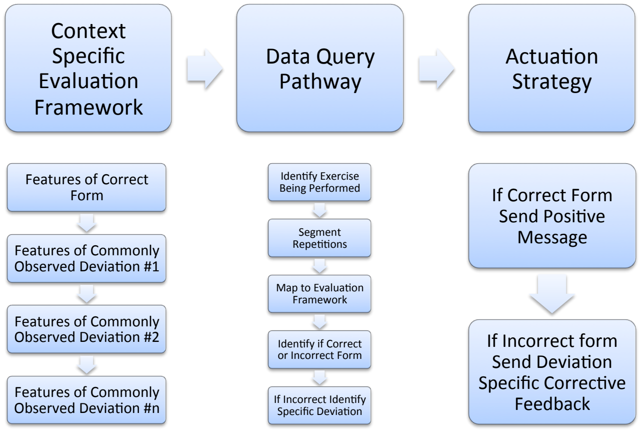

Figure 1. Steps involved in 'data to information' approach, using rehabilitation exercise performance evaluation and feedback example.

movement pattern. Initial classification will come in the form of correct or incorrect performance of the movement (binary level classification). Further classification will involve identifying the specific deviation if the movement is completed incorrectly (multi label classification). The steps involved in this data query pathway are outlined in section III.

Finally an actuation strategy must be put in place whereby the information is provided to the relevant stakeholder in an easy to understand and effective manner. This will differ depending on the end-user of the system.

III. METHODOLOGICAL APPROACH

Across all the application spaces described in this paper, the development of IMU based exercise classification systems consist of the following steps: data collection, pre-processing, segmentation, feature extraction and classification as can be seen in Figure 2. The following section provides a brief summary of each step.

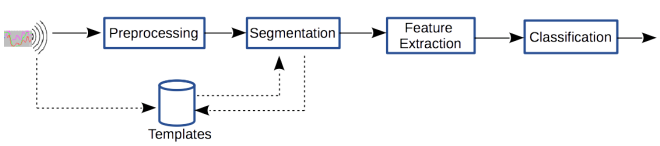

Figure 2: Steps involved in the development of an IMU based exercise classification system

A. Dataset Collection

In order to develop a high quality exercise analysis system a number of factors should be considered and optimised before completing a data collection. A preliminary study should be used to establish IMU positioning and settings: sampling rate, sensor ranges, data transfer and storage methods. In addition to identifying these aspects of study design, it is essential to ensure the IMUs are calibrated before all data collection sessions. Classification results are improved with larger data sets.

B. Pre-processing

The kinematic data contains two types of undesired noise: baseline drift and high frequency components. The high frequency noise is the elastic vibration in the fasteners used to mount the markers to the limb. This can be reduced by passing a specified order low-pass Butterworth with the normalised cut-off frequency for kinematics data. The drift noise is the long-term variation of baseline from straight lines. Therefore, the drift noise exists in all IMU data collected. The initial signal that is present when no movement occurs can be considered as noise data, we subtract its dimensional values from velocity and displacement or position data.

Following the removal of undesired noise from the kinematic signals, additional signals are often computed to gain additional information about the exercise being completed and improve classifier performance. Examples of such signals are the magnitude of acceleration, magnitude of rotational velocity and signals that describe the 3D orientation of the IMU such as pitch, roll and yaw or rotation quaternion values. These are computed from the IMU signals using methods such as complementary filters, gradient descent methods [7] and Kalman filters [8]. Linear acceleration may also be derived from the accelerometer data by removing the gravitational acceleration component.

C. Segmentation

Once the IMU data has been processed appropriately it is now important to segment the IMU data in to epochs that correspond to repetitions of the exercise being measured.

Due to a large amount of noise, synchronicity and variabilities of movement DoFs in the data stream via the IMUs, it is very challenging to effectively identify the movements of rehabilitation exercise. Many algorithms were introduced to segment the human motion for rehabilitation exercises, including the sliding window algorithm [9] top-down, bottom-up algorithms [10] zero-velocity crossing algorithms (ZVC), template-base matching methods [11] and the combination algorithms of the above [12] These algorithms have advantages and disadvantages. The ZVC-based algorithms are the fastest. However, the ZVC algorithm often truncates the movements. The based-template matching algorithms can more accurately identify the movements. However, the based-template matching algorithms are either much more sensitive with computation, or relies heavily on the templates.

In order to improve the performance in term of accuracy, memory and computational overhead, our group has recently introduced a fast segmentation algorithm. This segmentation algorithm consists of two main stages: movement trunk detection and the edge detection. In the first stage, the algorithm uses the ZVC algorithm to extract the ZVC points, next uses the Hidden Markov Models (HMM) with Viterbi algorithm to travel segments along the ZVC points and generate a sequence of states, then searches and combines segments into the movement trunks using the sequence of states. In the second stage, the algorithm searches the movement edges by comparing the velocity magnitudes of movement trunks to the ones of its neighbours and finally combines the trunks and edges in the full movements. Compared to the existing algorithms, the proposed segmentation algorithm does not keep the templates to search the movements. According to the different segment types and energy, it searches the trunks and edges of movements to avoid the over-segment problem.

D. *Feature Extraction*

Once exercise repetitions have been extracted, the systems extract a large number of features from each signal and each IMU. These features can be categorised into statistical features, information-theoretic features, frequency features and time-frequency features. Example statistical features include the mean, standard deviation, skewness, kurtosis, maximum, minimum, range, 25th percentile, 75th percentile and cross-correlation. Example frequency features are the 16 coefficients of the fast Fourier transform. Example time-frequency features are the 32 wavelet coefficients using the Daubechies 6 mother wavelet with level 5. Example information-theoretic features are the Lempel-Ziv complexity, cross-entropy and entropy rates. The exact features which produce the highest quality classification systems are unique to each specific exercise analysis problem. However, in general statistical features used in combination with frequency domain or time-frequency domain features produce the best classification scores. Feature selection or dimensionality reduction methods may also be applied to the feature set in advance of classification.

E. *Classification*

Following feature extraction classifiers can be developed and evaluated. Classification quality can be compared using features from multiple, subsets of and individual IMUs. This can inform the decision to use less IMUs in real-world systems in order to reduce overall system cost and increase system practicality. Leave one subject out cross-validation (LOSOCV) is most commonly used in the literature to estimate a classifier's ability to interpret data from new system users.

Supervised learning methods are employed for classification and commonly produce superior classification quality to unsupervised learning methods in exercise analysis. Methods such as Logistic Regressions (LR), Decision Trees (DT), Multilayer Perceptron Neural Networks (MLP-NN), Support Vector Machines (SVM), Random Forests (RF), k-nearest neighbours (k-NN) and Adaboost are used in our exercise classification systems. For each specific exercise analysis classification problem the method that produces the highest accuracy, sensitivity and specificity is chosen for use in the final, real-world system.

Table 1: Example results in exercise detection, binary exercise evaluation (acceptable versus any movement dysfunction) and multi-class movement dysfunction (acceptable or specific deviation) for multi-sensor and single sensor systems.
* denotes paper currently under review

		Single sensor			**All sensors**		
	Ref.	Acc (%)	Sens (%)	Spec (%)	Acc (%)	Sens (%)	Spec (%)
Exercise Detection	[14]	95	94	99	94	94	99
	(*)	94	93	99	99	98	100
Binary	[13]	73	58	82	83	75	88
	[15]	83	62	90	90	80	92
Multi-class	[13]	81	82	80	92	93	94
	[15]	40	43	95	70	70	97

Example results from our work are shown in Table 1. These results are taken from [13-15] and additional work currently under review. The table demonstrates the classification quality when using features computed from a full sensor set involving either three or five sensors and a single sensor.

IV. Application Models

A. *Exercise Performance Evaluation*

Previous work has evaluated data from multiple IMU sensors to classify exercise performance [16-18]. However, using multiple sensors reduces the usability of an IMU based platform in rehabilitation and conditioning, particularly if the platform is intended for use in the home. Our research therefore sought to investigate whether a single IMU sensor can provide sufficient data to be used in the development of an interactive exercise classification and feedback system. The results of this work demonstrated that a single IMU sensor is capable of classifying between seven different exercises with a high level of accuracy [14]. It was also shown that it is possible to classify between correct and incorrect performance of an exercise, and to classify the particular error in an exercise using data from a single IMU sensor with satisfactory levels of accuracy [1, 19]. This work also indicated that the addition of extra IMU sensors does not significantly improve results [14, 19].

These findings prompt the development of an interactive exercise classification and feedback platform using a single IMU sensor as an input for use in rehabilitation and S&C settings. An IMU based exercise system may increase client motivation while also improving exercise technique and adherence. IMUs can be used as part of an automated system to create accurate log entries that track exercise progress reliably. The sensors also allow for exercise sessions to be captured and saved in real time for immediate analysis, meaning coaches and rehabilitation professionals can adjust exercise programmes immediately. Furthermore the ability to transfer exercise logbooks to a cloud server would be useful for exercise professionals to track a client’s progress remotely. Using a single sensor is also desirable as it allows for the development of this system on a mobile platform.

B. Musculoskeletal Injury Risk Screening

Injury risk is heightened by the presence of aberrant movement during the performance of screening tests such as the FMS [2] and single leg squat [3]. To date these tools have been scored subjectively through the use of visual rating scales, some of which have only moderate levels of inter and intra rater reliability [4]. Furthermore, subjective evaluation of movement patterns leads to the potential for bias and/or measurement error. The process of screening is also time consuming for clinicians, particularly where there is a large amount of individuals (e.g. in a team setting).

Our work has demonstrated the potential for IMU based systems to automate screening tools meaning they can be rated with greater objectivity and in less time than previously possible. One IMU can classify performance in the single leg squat as acceptable or incorrect with 92% accuracy [6]. Furthermore, we have also shown the ability of a IMU based systems to quantify squat and lunge performance with moderate accuracy [1, 15]. These movements are commonly completed screening tools with variations of them used in the FMS. These results indicate a sensor-based system can potentially automate screening tools. This would allow clinicians screen multiple individuals faster and more reliably than previously possible.

V. Conclusions and Future Work

Our work has demonstrated that IMU based systems have the potential to accurately evaluate movement performance. Furthermore this has been completed with an emphasis on a minimal sensor set-up. This indicates that such systems could be used in exercise performance evaluation and injury risk screening tools. It is expected that future work will involve analysing an increased data set that incorporates other movements that relate to exercise performance and injury risk screening (e.g. deadlift). More sophisticated data analysis techniques should help improve accuracy and overall usability of such a system. This will allow IMUs to bridge the gap between laboratory and clinical based movement analysis, making it more cost effective and accessible than previously possible.

Acknowledgment

This project is partly funded by the Irish Research Council as part of a Postgraduate Enterprise Partnership Scheme with Shimmer (EPSPG/2013/574) and partly funded by Science Foundation Ireland (12/RC/2289).

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