

RESEARCH ARTICLE

Motion-core assistive tools using pervasive embedded intelligence

S. M. Namal Arosha Senanayake

IntelliHealth Solutions, University of Brunei Darussalam, Gadong, Brunei Darussalam



Correspondence to: S. M. Namal Arosha Senanayake, IntelliHealth Solutions, University of Brunei Darussalam, Gadong, Brunei Darussalam;
E-mail: aroshas@ieee.org

Received: March 31, 2021;

Accepted: May 8, 2021;

Published: May 12, 2021.

Citation: Arosha Senanayake SMN. Motion-core assistive tools using pervasive embedded intelligence. *Adv Comput Electron*, 2021, 2(1): 10-21. <https://doi.org/10.25082/ACE.2021.01.002>

Copyright: © 2021 S. M. Namal Arosha Senanayake. This is an open access article distributed under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by-nc/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.



Abstract: Real-time human movement monitoring anywhere at any time is time critical depending on core human motion activities, in particular nation's valuable asserts; athletes and soldiers considered as reference standard of any society. Light weight wearable technologies are the key measurements and instruments system integrated to develop human motion-core assistive tools (MAT) using pervasive embedded intelligence. Unlike many existing motion analysis models, motion-core models are based on domain specific data service architectures beyond cloud technologies using inner data structures and data models created. Four layered micro system architecture that consists of sensing, networking, service and Motion-core IoT (MIoT) is proposed. Knowledge base was designed as a distributed and networked data center based on transient and resident data addressing modes in order to guarantee the secure data accessing, propagating, visualizing and control between these two modes of operations. While transient data change and avail in relevant clouds storages, corresponding resident data and processed data retain inside local servers or/and private clouds. Data mapping and translation techniques are applied for the formation of complete motion-core data packet related to the test subject under consideration. Thus, hybrid MIoT system is developed using 3D decision fusion models which are the internationally quantifiable standards for assessing human motion data set by trainers, coaches, physiotherapists and orthopedics. MIoT built as motion-core assistive tools have been tested for rehabilitation monitoring, injury prevention and performance optimization of athletes, soldiers, and general public. The hybrid system introduced in this work is novel and proves lower down the latency and connectivity independence by allowing human movement analysis during daily active lifestyle.

Keywords: light weight wearable technologies, micro system architecture, motion-core IoT (MIoT), transient data, resident data, 3D decision fusion

1 Introduction

There were many motion analysis systems and methods introduced during past two decades [1–5]. But, few core human motion methods were addressed for real-time human movement monitoring anywhere at any time considered as time critical [6]. The necessity of biofeedback visualization and its control during actual human activities in real-time matters when it comes to nation's asserts; athletes, players and soldiers during training regime and international games [4, 7].

While biofeedback systems built during past two decades were gained the popularity among athletes, players and soldiers, custom made wearable technologies with pre-configuration based on anthropometry and race (in particular ASEAN vs Europeans and Americans) were critical in making biofeedback tools work efficiently [8, 9].

Most recent emerging field in data science led to the embedding necessary data models for biofeedback visualization and control using different machine learning algorithms [10]. These systems built were efficient as far as no latency and connectivity dependency arising from communication technologies, such as local wireless connectivity. Thus, working models were mostly in near real time (soft real time) allowing performance optimization of athletes, players and soldiers during their training regimes [4, 11].

The use of hybrid intelligence mechanism also played a crucial role during the past decade [12]. But, there were lack of evidences in the accuracy and precision of systems built as biofeedback systems for sports during performance enhancement and optimization [4, 13]. Data models were not sufficient to design these systems. There was a requirement to introduce decision fusion methods which are based on mainly qualitative international standards commonly used by trainers, coaches, physiotherapists, orthopedics, *etc.* lively involved during training

regimes and rehabilitation monitoring in clinical environment [14, 15]. Recently, IoT and cloud computing as novel tools were introduced in order to cater soft real-time human movement analysis [16].

Hence, core human motion as a time critical event under latency and connectivity independence is the critical problem addressed in this work. ASEAN athletics' are under considerable scrutiny on their performance enhancement and optimization due to lack of real time biofeedback tools. As a solution for these critical problem statements, motion-core assistive tools using pervasive embedded intelligence are introduced using domain specific data architecture made up of micro-layer architectures executable interactively using Motion-core IoT based on transient and resident data processing modes.

2 MAT data service architecture

Motion-core Assistive Tools (MAT) data service architecture follows the principle behind decentralized and distributed network architecture. Most of the layered architecture defined in network architectures are primarily dependent on the services provided by below and upper layers subject to protocols established in each layer. This will allow to define functions of each layer while they are governed by mostly headers and trailers of each layer considered. Thus, availability and accessibility of data in each layer are restricted according to services and protocols established. This leads not only the constraints to real-time data processing, as well as connectivity dependence of each layer, such as TCP/IP protocols.

MAT data service architecture is novel and it is fully dependent on data services than functions and protocols defined in each layer. This allows not just the accessibility and availability of data in each layer, it also allows biofeedback visualization and control depending on the actual status of core human motion. In order to accommodate efficient usage of data, defining micro architectures are essential such a way that data models required in a decentralized and networked environment differ depending on the data accessibility and availability for different data processing. Thus, data model must be guided depending on core motion activities happening in real-time.

Therefore, data service architecture introduced in this work addresses the research gap between biofeedback visualization and control by availing the data depending on the actual motion-core activity in real time such a way that healthcare professionals intervene in different sports during training regimes and actual games involved and in case of elderly remotely by switching the networks.

Furthermore, secure data is another research gap since profile data of athletes, players and soldiers are from one side vulnerable to attack and as well their profile data are useful to duplicate, replicate easily using necessary advanced technologies currently available such as motion capture system. In this research, data security is guaranteed in addition to the network security features available in a connected environment by introducing two different data processing modes; transient and resident.

Thus, mapping and translation of data addressed is novel and it is a partially satisfying requirement of light weight wearable technologies adapted to these kind of domains, such as sports, than leaving the complete data transformation as a data processing tasks in a computing environment.

Figure 1 illustrates micro architecture introduced as a data service architecture that can be used in a motion-core environment in order to address the accessibility and availability of data for biofeedback.

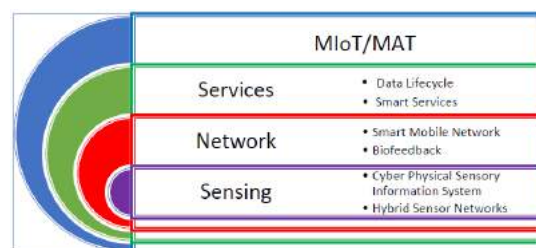


Figure 1 Data Service architecture for motion-core environment

The micro architecture in Figure 1 is processed in a local storage or/and cloud if the motion-core binds at a server. But, when motion-core binds at a mobile platform, micro architecture is

processed in a networking environment using secure two modes of data processing introduced in this research.

2.1 Sensing layer

Based on lightweight wearable sensors worn interfaced with Motion-core IoT (MIoT), sensing layer is responsible for ingesting raw sensor data acquiring from various different multiple sensing sources such as MIoT, lightweight wearable sensors, motion capturing sensors, *etc.* Sensing layer created allows any sensor to integrate for motion analysis. Thus, MIoT works as a biofeedback tool interactively using transient data which is a solution introduced for secure data accessibility during biofeedback. Transient data contain intelligent identification code (IIC) as the transformed identification code of actual test subject under consideration together with actual motion-core data based on the current status of motion. On contrary resident data contain IIC together with historical motion-core data under the control of relevant healthcare professionals in a local secure storage. Hence, IIC is designed using 64 digits in which 32 digits are stored as transient IIC and another 32 digits as resident IIC.

2.1.1 Hybrid sensor networks

Data service architecture defines hybrid sensor networks such a way that ingesting data shall be done independent of the origin/source of raw sensor data acquired. Thus, the formation of sensor network is a wireless adhoc network which allows the connection of MIoT as a sensor node for acquiring raw sensor data at the physical layer as illustrated in Figure 2.

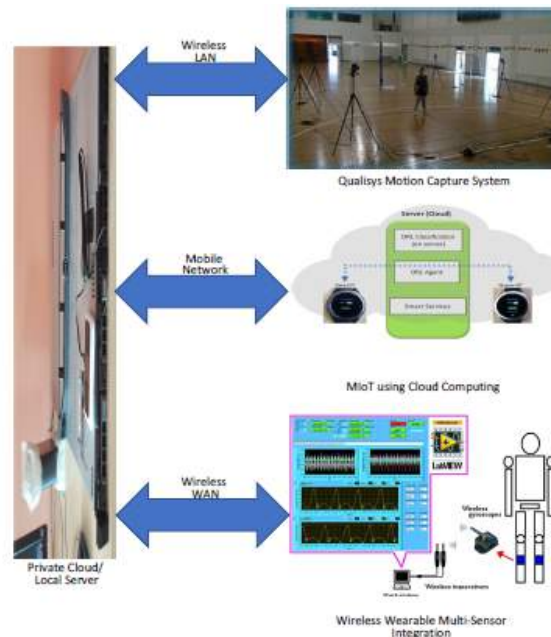


Figure 2 Hybrid sensor network

Qualisys motion capture system is connected using wireless LAN for transmission of real world coordinates of reconstructed 3D image data. Wireless WAN is used for data transmission of wireless wearable sensor suit that can contain motion, EMG and EEG sensors. MIoT is connected using mobile network connectivity as per mobile operator of choice in order to transmit raw data related to biofeedback. All raw sensory data are considered as the input data for the embedded system. While local server acquires all these raw data, it is also connected to the cloud using the same mobile operator in order to do necessary cloud computing as shown in Figure 2. The connectivity of all sensors are allowed the acquisition of raw data for all human activities; rehabilitation monitoring, injury prevention and performance optimization in outdoor and indoor in real-time.

2.1.2 Cyber physical sensory information system

It is a repository of multi-sensor data stored as a pattern mining predictor system (PMPS) using data fusion techniques. PMPS allows mapping and visualization of fused sensor data into

all upper layers including to MIoT and MAT. Thus PMPS is designed in order to synchronize and interface with centralized server as depicted in Figure 2 and at the same time the availability of fused data in cloud environment. Fused sensor data shall be obtained using different transformation techniques which are already embedded inside the centralized server such a way that the most suitable transformation technique is retrieved from the server. In this research, previously designed evolving case library which is stored in the server uses for the appropriate sensor selection based on the actual sensor worn by the test subject. Therefore, PMPS shall be defined as shown in Equation (1);

$$PMPS_i = \sum_{i=0}^n f(motion_i + sensormotion_i + sensoremgi + sensoreegi + MIoT_i) \quad (1)$$

where;

i: i^{th} test subject

n: number of test subjects

PMPS_i: Pattern Mining Predictor System for i^{th} test subject

motion_i: fused data from motion capture system of i^{th} test subject

sesnoremg_i: fused data from EMG sensors of i^{th} test subject

sensoreegi_i: fused data from EEG of i^{th} test subject

MIoT_i: Motion-core IoT of i^{th} test subject

2.2 Network layer

The service provides by the network layer is critical depending on the server connectivity to wireless networks and mobile connectivity. The solution proposed in this research work optimizes communication technologies by lower down the latency and connectivity independence. There are two main functions realizing in this layer; smart mobile network and biofeedback. While smart mobile network is the basis to establish the connectivity during the training regimes, biofeedback is based on the actual activity happening using the connection categories illustrated in Figure 2.

2.2.1 Biofeedback

Managing transient data during the actual activity happening is the responsibility of biofeedback. While PMPS is responsible to store fused data in relevant storage (cloud or/and server), biofeedback allows the transportation of fused data to the relevant destinations that can be to the services layer and as well as directly to the MAT based on the need to intervene by a relevant healthcare professional timely manner. Therefore, MAT can act as a biofeedback visualization and control in order to adjust and fine tune relevant parameters reflected in fused data from PMPS. Since transient data is considered during actual activity happening, motion-core data bind at mobile platforms. Data service architecture related to transient data is processed and visualized using relevant MAT. Thus transient data IIC reflected at this layer contains the current status and classification based on the performing activity as illustrated in Figure 3 that is a mapping and translation of resident data IIC into transient data IIC during binding at a mobile platform. In this research Android platform is used as mobile platform and Samsung IoT connected via Bluetooth is used for biofeedback visualization and data control. Therefore, biofeedback involves in real-time operations than off line and online operations during motion-core relevant actual activities performing and monitoring in real-time.

BY	RCODE	DATE	TIME	STATUS & CLASS	BMDS	CCODE	T
1 9 6 3	3 7 1 3	3 0 3 2 1	1 0 9	0 8 7 4 9 1 3	4 2 6 1	1 4 1 0	1

Figure 3 Transient data

Where;

BY: Birth Year

RCODE: Residence area code

DATE: Date of actual experiment

TIME: Time of actual experiment

STATUS & CLASS: Actual status and classification of i^{th} test subject

BMDS: Birth month, date and sex

CCODE: Clinic area code (if it is in the residence RCODE = CCODE)

T: Type of clinic (0 = residence, 1 = hospital, 2 = polyclinic, 3 = clinic, 4 = private clinic)

Therefore, biofeedback involves in real-time operations than off line and online operations during motion-core relevant actual activities performing and monitoring in real-time.

2.2.2 Smart mobile network

The responsibility of the formation of case library based on PMPS is executed using smart mobile network during training regime. Based on the historical pattern set, case library is formed in order to extract and retrieve the most matching pattern during the actual activity happening. Thus, case library is implemented in a SQL server within the server configured as shown in Figure 2. Resident data are directly involved for the formation of a comprehensive case library which allows to extract relevant matching pattern from PMPS using case based reasoning. Data service architecture used for resident data IIC processing binds at local or/and cloud server depending on communication method used as shown in Figure 2. In this research hybrid communication methods are applied due to wireless LAN, Mobile networking, and wireless WAN required for multi-sensor integration and data fusion during the formation of case library. Figure 4 illustrates resident data IIC used in smart mobile network.

BY			RCODE			LEARNT DATE			CYCLE			STATUS & CLASS				BMDS			CCODE			T									
1	9	6	3	3	7	1	3	3	0	1	2	1	1	0	9	0	6	5	4	4	3	1	4	2	6	1	1	4	1	0	1

Figure 4 Resident data

Where;

BY: Birth Year

RCODE: Residence area code

LEARNT DATE: Last date of training regime

CYCLE: Number of times updated with a novel pattern set during training regime

STATUS & CLASS: percentages of rehabilitation, injury prevention and performance

BMDS: Birth month, date and sex

CCODE: Clinic area code (if it is in the residence RCODE = CCODE) during training regime

T: Type of clinic (0 = residence, 1 = hospital, 2 = polyclinic, 3=clinic, 4 = private clinic)

2.3 Services layer

The extract of relevant transient and resident data by the end user is executed in this layer. Depending on whether MIoT or/and MAT, the data is transformed into the tools interfaced using pervasive embedded intelligence. Some pattern set shall be reflected as the reuse pattern set from the case library formed for the monitoring of test subject under consideration by the relevant healthcare professionals. On the other hand, novel pattern set would have been generated during actual performing activities which do not exist as a pattern set in the case library, leading to retain as a new pattern set in the case library. Thus, service layer provides two different types of services; smart services and data lifecycle.

2.3.1 Smart service

Primary function is to map processed data using different visualization techniques based on the tools interfaced into the system. The tools used so far are different displays/TV screens, Android devices and Samsung IoT in real-time which work as MIoT or/and MAT. While MIoT possesses dual functional capabilities during biofeedback visualization as a visualization tool for the MIoT layer and at the same time during biofeedback control as a data control tool for all below layers, including the bottom most layer, sensing layer. But, MAT uses pervasive embedded intelligence which facilitates to make the most appropriate decision at MAT layer.

2.3.2 Data lifecycle

Primary goal of MAT is to establish case library using PMPS while maintaining the case library using pervasive embedded intelligence. As per data service architecture introduced in Figure 1, embedded intelligence is developed by the formation of comprehensive case library for each test subject under consideration during training regime such a way that case based reasoning is applied to extract the matching pattern set from the case library. At the same time, the availability of this pattern set across all communication methods illustrated in Figure 2 during training regime for each test subject using IIC facilitates to revise/retain/reuse during the data lifecycle process. Thus, pervasive embedded intelligence is essential for data lifecycle.

2.4 MIoT/MAT layer

Unlike other systems developed, MIoT/MAT layer is not solely an output or/and report generation of a test subject from the case library formed, it is about the data lifecycle of

the case library formed during training regime and actual performing activity based on core human motion. Therefore, hybrid MIoT is introduced for producing the output and data control necessary all below layers of data service architecture in Figure 1. This is possible due to the implementation of IIC relevant to transient data and resident data for the PMPS formed in order for secure transmission required based on hybrid communication methods used as per Figure 2 for different motion-core activities in real-time. Thus, data availability is guaranteed efficiently and securely by lower down the latency and connectivity independence using pervasive embedded intelligence than knowledge engineering and data driven approached used with lacking of real-time systems capabilities. MIoT and MAT provide the interfacing of smart devices with inter-operability capabilities in a secure manner due to IIC novel coding scheme introduced for transient and resident data.

Mapping the pattern set extracted from case library into MIoT/MAT was done using 3D fusion matrix. 3D fusion matrix defines as the decision making is the translation of motion-core activity based on three important rule based decisions; current status and classification of transient data, resident data, and internationally quantifiable assessment criteria given by trainers, coaches, physiotherapists, and orthopedics. Therefore, 3D decision fusion matrix shall be defined as illustrated in Figure 5. In the 3D decision fusion matrix, classes are defined as follows;

Class A = Healthy test subject

Class B = Rehabilitation or performance optimization is required. Based on two test cycles performed, the percentage of actual status is below 60% of mean class defined.

Class C = Rehabilitation or performance optimization is required. Based on two test cycles performed, the percentage of actual status is below 40% of mean class defined.

Class D = Rehabilitation or performance optimization us required. Based on two test cycles performed, the percentage of actual status is way below 20% of mean class defined.

Classes A, B, C, and D are reflected in the transient IIC and resident IIC as 1, 2, 3, and 4 respectively due to solely digits considered for IIC definition.

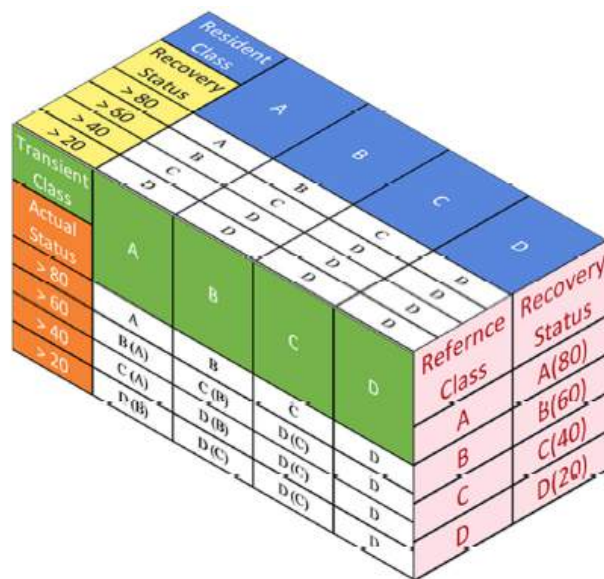


Figure 5 3D decision fusion matrix

In Figure 5, resident class and recovery status were obtained with respect to reference class and recovery status defined by trainers, coaches, physiotherapists, and orthopedics. Therefore, case library is formed using semi-supervised reinforcement learning methods with deep neural network architecture. Retaining a new pattern set in the case library subject to supervised learning using reference class with corresponding recovery status while the decision making to whether the pattern set belonging to the respective resident class with respective recovery status is subject to reinforcement learning. Hence, appropriate associative rules defined between reference class and resident class are the basis for decision fusion during training regime.

Transient class depends on the actual status during actual clinical trial. Thus, actual class defines using associate rules shown in Figure 5. As an example C(A) implies the actual class; Class C associates with Class A depending on the rehabilitation achieved and monitored by health professionals during post-surgery or in case of athletes and players, optimum performance

is monitored by trainers and coaches using MIoT or/and MAT tools.

Further, a novel pattern set shall be identified using decision fusion between transient class and reference class by applying case based reasoning. The retrieval of the best matching pattern set from case library subject to the proven decision fusion carried out. While the actual status of a transient class is governed by associate rules, recovery status in the reference class is based on the percentage defined in a respective class (As an example reference class A is based on recovery status class A subject to minimum of 80% achievement of motion-core activity monitored by healthcare professionals). If there is no pattern found, novel pattern set is retained as a new case in the case library updating accordingly resident class and its respective recovery status. By inserting a new case into the case library requires to undergo the training using semi-supervised reinforcement learning. Therefore, 3D decision fusion matrix illustrated in Figure 5 is implemented using hybrid intelligence leading to successful development of MIoT and MAT based on pervasive embedded intelligence. While MIoT is executed in hybrid mode using transient and resident classes, MAT works as a biofeedback visualization tool for the test subject and for healthcare professional during actual motion-core activity in real-time.

3 Experimental set up and methodology

Proving of MAT data service architecture is carried out by setting up the experiment using all communication methods; wireless LAN, wireless WAN, and mobile network as illustrated in Figure 6, Figure 7 and Figure 8 respectively.



Figure 6 Wireless LAN

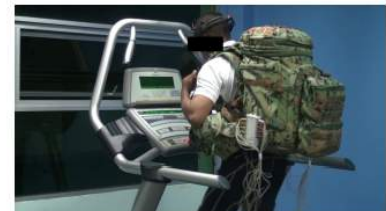


Figure 7(a) EMG and Motion Sensors

Figure 7(b) EMG and EEG Sensors

Figure 7 Wireless WAN



Figure 8 Mobile network

Figure 6 represents the employing Qualisys Motion Capture System with wireless EMG for indoor game training regime using wireless LAN connectivity. Figure 7 illustrates worn wireless EMG, EEG and Motion sensors on treadmill walking using wireless WAN connectivity.

Figure 8 shows the employability of smart shoes from ZeBlok as an IoT directly connected to the AWS cloud for real-time data acquisition using local mobile operator connectivity based on Android mobile platforms and Samsung IoT worn by the test subject. In this manner, with the support of sports medicine and research center, Brunei and ministry of defense, Brunei real world experiment were set up in order to first form the Pattern Mining Predictor System (PMPS) and then followed by the Case Library (CL). All experiment were carried out using athletes, players, and soldiers who are considered as reference standard of any society. The routine the soldiers went through this experiment set up was 40 soldiers during the training regime of one month despite number of athletes and players are not so appealing in Brunei context mainly due to athletes and players are mostly soldiers as well. The local and cloud server contains approximately 6TB of raw data securely stored using IIC implemented. At any level of data service architecture, the only raw data accessible using transient IIC data only. Thus, resident IIC data retains in the local and cloud server with the only accessible to the system administrator preventing security breaches over vulnerable data. This article does not intend to provide the insight into cyber security features embedded into MAT.

CL is based on different types motion-core activities performed by the test subject. While the testing of pattern sets stored in CL is not comprehensive enough, novel pattern sets are stored in the CL based on new types of motion-core activities identified and defined by relevant healthcare professionals, trainers, coaches, physiotherapists, and orthopedics. Thus, CL shall be defined as follows;

$$CLi = \sum_{i=0}^n (RMi + IPi + POi) \tag{2}$$

Where;

i: i^{th} test subject

n: number of test subjects

CLi: Pattern set of i^{th} test subject in the case library

RMi: Rehabilitation Monitoring of i^{th} test subject based on 3D fusion matrix

IPi: Injury Prevention i^{th} test subject based on 3D fusion matrix

POi: Performance Optimization i^{th} test subject based on 3D fusion matrix

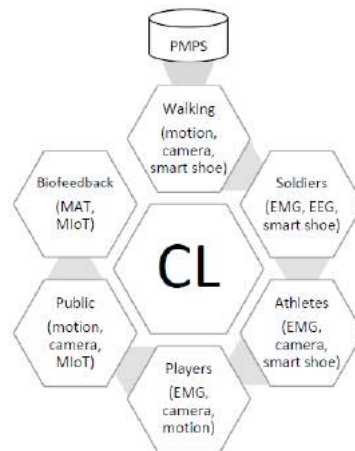


Figure 9 Case library

The CL in equation 2 defines based on the test subject under consideration. But, CL contains different databases depending on each motion-core activity performed. As illustrated in Figure 4 and Figure 5, walking activity is defined using numerical value zero (0) binding with status and class digits.

Having formed CL, it was trained using semi-supervised reinforcement learning based on deep neural network (DNN) topologies used for different motion-core activities. There is no general one topology applied for the complete CL. It depends on the type of motion-core activity and based on built in data fusion algorithm chosen (from set of fusion algorithms available in the local server and cloud server as illustrated in Figure 1) used for the formation of PMPS. Figure 9 shows the algorithm implemented for CL formation during training regimes;

There are five categories of motion-core activities are analyzed as illustrated in Figure 9. They are numbered from 0 – 4 using numeric values for the definition of transient and resident IIC defined in Figure 3 and Figure 4 by binding together with status and class during training regime. The sixth category shown in Figure 9, biofeedback is subject to the novel pattern

identified during testing stage which shall be retained as a new case in CL subject to retraining and amending respective resident data and its respective IIC in the CL.

4 Experimental results

There are comprehensive results to demonstrate the success of MAT using pervasive embedded intelligence based on athletes, soldiers, and general public during their visits to rehabilitation clinics. But, MAT has been successfully tested in Malaysia and Japan based on the MoUs signed between Universiti Malaya Connected Health (UMCH) Sdn Bhd and Gifu University, Japan.



Figure 10 MAT for a soldier (a) Actual test subject; (b) MIoT for biofeedback; (c) All case records from CL

MAT proves for a soldier who is recovering from ankle foot injury is illustrated in Figure 10. Figure 10 (a) shows the periodical test carried out after 6 months of foot injury. The expectation is to retrieve a similar case from case library already trained. Using all known cases as demonstrated in Figure 10 (c) which is obtained from CL using LabVIEW interface in real-time, 3D decision fusion matrix maps into Samsung Gear S3 smart watch (courtesy from Samsung Asia Pte Ltd) as MIoT for biofeedback shown in Figure 10(b), the soldier’s actual health status as Class B (65%) recovered compared to the transient health status reported as Class C (75%). Thus, results proves the efficiency of using MAT using pervasive embedded intelligence based on mapping a case from CL by applying 3D decision fusion matrix. These results allow physiotherapist to adjust protocols used for rehabilitation monitoring leading to performance optimization of actual motion-core activities (walking) during next clinical visit.

Figure 11 shows the use of MIoT shoe from Zeblok for cadence analysis of an athlete. MIoT shoe has a built in router located at the heel of the smart shoe connected with four different sensors at the toe (Z1), left ball (Z2), right ball (Z3), and heel (Z4). During motion-core activity, raw data are directly uploaded into the AWS cloud. In this work, cadence analysis was carried

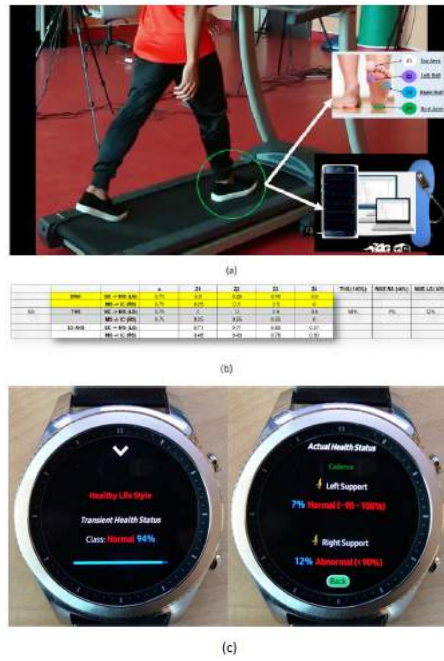


Figure 11 MIoT using 4G mobile connectivity (a) Smart shoe worn athlete; (b) Cadence analysis; (c) MAT using Samsung smart watch

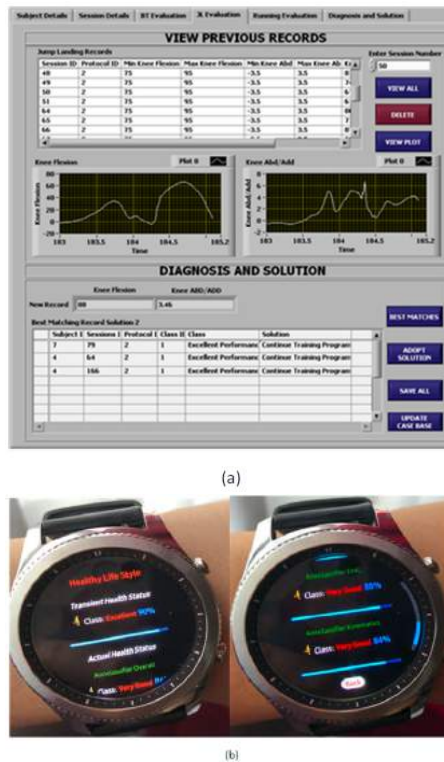


Figure 12 MAT for Jump Landing; (a) Previous CL records; (b) MIoT for biofeedback

out by storing all cases in the CL similar to the sample spreadsheet given in Figure 11(b). Unlike Figure 11(c), storing all cases using LabVIEW interface in real time is not required for this work. Cadence analysis was carried using right and left support by ignoring double support since any abnormality is subject to swinging of either right or left foot. This is occurred during left or right support. As MAT reports using Samsung Gear S3 smart watch, this athlete has clear abnormality in the right support due to 12% mean square error (MSE) reported. During walking the MSE larger than 10% implies the test subject missed out one phase in a gait cycle. Thus, left

support and right support holds 40% each with double support of 20% to form 100% cadence. Therefore, actual health status of this athlete is abnormal in his right support.

Figure 12 illustrates the use of MAT during a training regime for a netball player using wireless LAN connectivity. Figure 6 represents trainer forcing to do a jump landing during a ball throw. Based on the jump landing motion-core activity and trained CL, previous records shall be retrieved using LabVIEW interface in real-time as illustrated in Figure 12 (a). Therefore, the most matching case is retrieved for the actual jump landing motion-core activity using 3D decision fusion matrix implemented as illustrated in Figure 5. The result is mapped into MIoT for biofeedback visualization based on ANN classifier using Samsung Gear S3 smart watch during the training regime as shown in Figure 12 (b). As per actual status, the player is a very good player (84%-88%) compared to excellent performance with 90% as per previous records retrieved and shown as transient health status in Figure 12(b). The results allow player to improve the performance to reach the optimal performance during subsequent training regime under the monitoring of trainer using MAT before player will play in an actual competition.

5 Discussion and conclusion

Pattern Mining Predictor System (PMPS) is successfully built as a cyber physical sensory information system in the centralized server while Case Library (CL) is efficiently created addressing different communication modes; wireless LAN, wireless WAN, and mobile network depending of combinations of sensors worn for a motion-core activity under consideration during a training regime. Thus, CL is formed using five different motion core activities defined and sixth category is a completely novel method for biofeedback using Motion-core Assistive Tools (MAT) based on pervasive embedded intelligence and Motion-core IoT (MIoT). MAT and MIoT prove that they can lower down the latency and connectivity independence during actual testing in real-time compared to the training regime that was carried out in this work offline, online and near real-time (4G mobile connectivity used in MIoT shoe). Novel 3D decision fusion matrix was implemented in order to retrieve the best matching case from CL using semi-supervised reinforcement learning.

Experimental results prove that the successful implementation of data service architecture for motion-core environment. Intelligent Identification Coding (IIC) scheme was introduced to secure test subjects involved by storing all motion-core data in two different modes of operations; transient data and resident data. Therefore MAT using pervasive embedded intelligence was proven for rehabilitation monitoring, injury prevention, and performance optimization of soldiers, athletes, players, general public visiting rehabilitation clinics during training regimes for the establishment of CL and actual testing in real-time. MAT was also tested in Malaysia and Japan based on necessary agreements signed.

As future work MAT is planning to expand for elderly and children in order for healthcare professional and parents monitoring critical actual motion-core activity happening remotely in real-time using MIoT as a biofeedback tool.

Ethics

Ethics clearance was obtained from University of Brunei Darussalam by signing off standard ethics clearance form provided by the research office. Furthermore, ethics clearance for national athletes, soldiers, and players was obtained by sports medicine and research center and ministry of defense, Brunei. Patients visited rehabilitation clinics were signed off their voluntary participation in this work by respective physiotherapists and orthopedics involved from relevant clinics.

Conflict of Interest and Funding

There is no conflict of interest. This publication is part of the output of the ASEAN Institutes of Virtual Organization at National Information and Communications Technology (NICT), Tokyo, Japan; ASEAN IVO project with the title "*IoT system for Public Health and Safety Monitoring with Ubiquitous Location Tracking*". This research is also partially funded by the University Research Council (URC) grant scheme of Universiti Brunei Darussalam under the grant No: UBD/PNC2/2/RG/1(195). Samsung Gear S3 classic smart watches used in this research are fully sponsored by Samsung Asia Pte Ltd.

Acknowledgements

Author sincerely acknowledges and appreciates the support and cooperation received from the staff of Ministry of Defence, Bolkiah Garisson as well as Sports Medicine and Research Centre (SMRC) of Brunei Darussalam. Special thanks go to all soldiers, athletes, players, and general public/patients who voluntarily and patiently participated in this study. Specific mention of two persons in appreciation of their tremendous support throughout this research, Ms. Michelle Basir and Mr. Illepurma Ranasinghe, physiotherapist and the head physical and strength conditioning at Ministry of Defence, Brunei Darussalam, respectively.

References

- [1] Gravina R, Alinia P, Ghasemzadeh H, *et al.* "Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges. *Information Fusion*, 2017, **35**: 68-80.
<https://doi.org/10.1016/j.inffus.2016.09.005>
- [2] Ji X and Liu H. Advances in View-Invariant Human Motion Analysis: A Review. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 2010, **40**(1): 13-24.
<https://doi.org/10.1109/TSMCC.2009.2027608>
- [3] Mariani B, Jiménez MC, Vingerhoets FJG, *et al.* On-Shoe Wearable Sensors for Gait and Turning Assessment of Patients With Parkinson's Disease. *IEEE Transactions on Biomedical Engineering*, 2013, **60**(1): 155-158.
<https://doi.org/10.1109/TBME.2012.2227317>
- [4] Kruk E and Reijne MM. Accuracy of human motion capture systems for sport applications; state-of-the-art review, *European Journal of Sport Science*, 2018, **18**(6): 806-819.
<https://doi.org/10.1080/17461391.2018.1463397>
- [5] Liu S, Zhang J, Zhang Y, *et al.* A wearable motion capture device able to detect dynamic motion of human limbs. *Nat Commun*, 2020, **11**: 5615.
<https://doi.org/10.1038/s41467-020-19424-2>
- [6] Alahakone AU and Senanayake SMNA. A Real-Time System with Assistive Feedback for Postural Control in Rehabilitation. *IEEE/ASME Transactions on Mechatronics*, 2010, **15**(4): 226-233.
<http://ieeexplore.ieee.org/document/5420032>
- [7] Senanayake SMNA, Kadir NH, Suhaimi MSAB, *et al.* Master-Slave IoT for Active Healthy Life Style. *Proceedings of 12th IEEE Conference on Human System Interaction*, 978-1-7281-3980-7/19/\$31.00 ©2019 IEEE, 2019, 155-161.
<https://doi.org/10.1109/HSI47298.2019.8942640>
- [8] Senanayake C, Senanayake SMNArosha. A Computational Method for Reliable Gait Event Detection and Abnormality Detection for Feedback in Rehabilitation, *Computer Methods in Biomechanics and Biomedical Engineering*, Taylor & Francis, 2011, **14**(10): 863-874.
<http://www.tandfonline.com/doi/abs/10.1080/10255842.2010.499866>
- [9] Hewett TE, Stasi SLD and Myer GD. *American Journal of Sports Medicine*, 2012, 216-224.
- [10] Lauer R, Smith BT and Betz RR. Application of a neuro-fuzzy network for gait event detection using electromyography in the child with cerebral palsy. *IEEE Trans Biomed Eng.* **52**: 1531-1540.
- [11] Arosha Senanayake SMN and Wulandari P. "Soft Real Time Data Driven IoT for Knee Rehabilitation." *2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA)*, 2020, 1-7.
<https://doi.org/10.1109/CITISIA50690.2020.9371780>
- [12] Senanayake SMNA, Malik OA, Iskandar PM, *et al.* A Knowledge-Based Intelligent Framework for Anterior Cruciate Ligament Rehabilitation Monitoring. *Journal of Applied Soft Computing* (impact factor 2.140), Elsevier, 2014, **20**: 127-141.
<http://dx.doi.org/10.1016/j.asoc.2013.11.010>
- [13] Munro BJ, *et al.* The intelligent knee sleeve: a wearable biofeedback device. *Sens. Actuators B Chem*, 2008, **131**(2): 541-547.
- [14] Khudson D. Applying biomechanics in sports and rehabilitation, Chapter 12, in *Fundamentals of Biomechanics*, 2007, 245.
- [15] Gouwanda D and Senanayake SMNA. Periodical gait asymmetry assessment using real-time wireless gyroscopes gait monitoring system. *Journal of Medical Engineering & Technology*, 2011, **35**(8): 432-440.
<https://doi.org/10.3109/03091902.2011.627080>
- [16] Sharma S, Chen K and Sheth A. Toward Practical Privacy-Preserving Analytics for IoT and Cloud-Based Healthcare Systems. *IEEE Internet Computing*, 2018, **22**(2): 42-51.