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Procedia Engineering 34 (2012) 367 – 372

Procedia Engineering

www.elsevier.com/locate/procedia

9th Conference of the International Sports Engineering Association (ISEA)

Technology and health: Physical activity monitoring in the free living environment

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Accepted 06 March 2012

Abstract

The use of remote sensing technologies and software is well established in the sports domain. These technologies may include inertial sensors, magnetometers, GPS and wireless technologies, or a combination of such devices. Detailed activity information, sports biomechanics and performance measures can be extracted as a tool for athletic coaching and technique assessment.
In the domain of health, there is growing interest in leisure time physical activity as a preventative measure to combat inactivity, obesity and onset of cardiovascular disease in the adult population. This has lead to recent interest in the quantification of physical activity and daily energy expenditure in community life. Metrics such as activity banding, gait quantification and daily energy expenditure are directly relevant to the promotion of a healthy lifestyle.
This paper introduces some challenges in deploying existing wearable sensors for sports performance into the healthcare domain. These challenges include user requirements and technical competence, extended duration monitoring and working within a biomedical rather than sporting culture. A test protocol using multiple inertial sensors was developed and tested in a single case study to investigate the validity of the method.

Keywords: Inertial sensors; free living; energy expendature

1. Introduction

An emerging interest in healthcare is the desire to assess leisure time physical activity both in the healthy general population and in patients, since such physical activity or exercise has a direct impact on

1877-7058 © 2012 Published by Elsevier Ltd.
doi:10.1016/j.proeng.2012.04.063

their wellness and future risk of cardiovascular disease. Of particular interest is exercise or physical activity undertaken post-operatively [1], where the positive effects of exercise can hasten recovery. Of particular interest to the authors is how remote sensing technologies can be utilised as a diagnostic tool in obesity [2] and understanding the effects of some cancers on upper body function [3].

Inertial sensors, including accelerometers and gyroscopes have been used in sporting applications to quantify athletic performance at the elite level [4]. They have also been used to measure physical activity, and have been validated against metabolic gas analysis both in the laboratory [5] and in the field environments [6]. Video capture motion analysis has been a powerful tool to validate these sensors' quantification of human physical activity. Standard off the shelf cameras are suitable for such validation [7] and have revealed inertial sensors are useful tools as an adjunct to more conventional technologies.

Typically the use of these sensors in elite sports performance means that they must collect data for a few hours at most, but at a rate consistent with sporadic movements and high-acceleration dynamics. However in the community environment, devices to quantify leisure time physical activity need to be "wearer transparent" in an operational sense, and may need to run for much longer periods of time. In the chosen application area, the sports sensors were used to investigate and reduce the amount of data capture as well as to devise computationally simple algorithms that could be built into the devices themselves. The advent of smart phones with these sensors built in offers the opportunity to deploy technologies that already have significant market penetration [8].

2. Methods

2.1. Technology and algorithm development

The sensors used for this experiment were the next version of our in-house design [9] and included on-board memory, radio synchronisation and tri-axial accelerometers and gyroscopes. The platform is 'match box' in size and taped to the limbs equidistant between joint segments. Data from the sensors was downloaded into MATLAB for pre-processing and filtering. The algorithm was developed and implemented using the ADAT toolbox [10].

Activity classification was developed through a combination of sensor orientation and detection of characteristic limb movements through unique signatures. The methodology is shown in Figure 1. In general, posture orientation was derived by finding beginning and endings for activities based on maximum and minimum values in first-order differentiated axes, specific to sensor placement. Windows were used to find the average orientation of the sensor. Quantising was applied to determine posture orientation whereby ± 45 degrees within vertical was classified as standing, ± 45 degrees of horizontal was classified as sitting/laying down. To differentiate between sitting/horizontal, sensor data from the ankle sensor was utilized.

Activity onset first does gross activity classification then subdivides them into smaller more specific activities. Thresholding was applied specific to posture orientation and body segment. The thresholds eliminated the noise associated giving the beginnings and endings of each individual activity. Peak detection in the sliding window used a median value to avoid spurious signals and activities were overlapped for robustness and to avoid missing onsets of new activities. The peaks found were those above the median of the window. All data was passed through all classifiers to assess false positives and negatives.

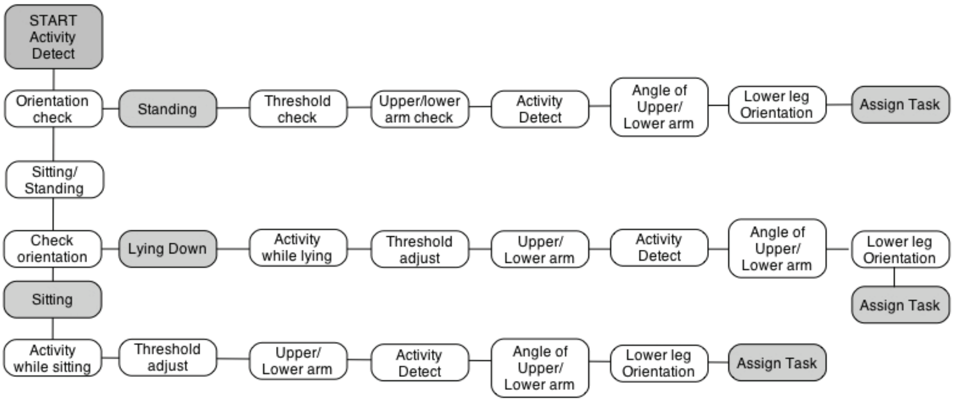

Fig. 1. Flow chart of algorithm and then use below description

2.2. Study Design

Fourteen movement tasks were identified from the literature as representative of physical activities of interest (Table 1). A subject was instructed in these tasks and given an opportunity to practice them. Each trial was an individual movement task repeated 10 times and synchronized with video by mechanical artefact. And additional task of randomized activities chosen from the 14 task sets was completed by the subject as a "free living" task (task 15). The inertial sensors (tri-axial) were placed on the upper arm, lower arm and upper leg and ankle. Sensors were aligned such that the 1st accelerometer was pointing in the direction of gravity for a standing subject (i.e. g_z) at the start of each trial.

Table 1. Daily living tasks by body position

STANDING	SITTING	LYING DOWN
1. Reach overhead as though reaching for object off high shelf so that arms are fully extended.	6. Reach overhead as though reaching for object off high shelf so that arms are fully extended.	11. Hold arms as though holding book
2. Reach overhead as though reaching for object off shelf at 'head' level' so that hands are high but 60 deg forward flexion about the shoulders.	7. Reach overhead as though reaching for object off shelf at 'head' level' so that hands are high but 60 deg forward flexion about the shoulders.	12. Reach vertically as high as possible
3. Reach forward as far as possible at shoulder height	8. Reach forward as far as possible at shoulder height	13. Reach behind head
4. Reach to back of head (like combing hair at back of head) – for this movement, the wrist will be above 90 but shoulder flexion will be about 90.	9. Reach to back of head (like combing hair at back of head) – for this movement, the wrist will be above 90 but shoulder flexion will be about 90.	14. Stretch arms behind head as far as possible
5. Reach forward at waist height to pick object up off surface.	10. Reach forward at waist level to pick object up off surface.	

3. Results

3.1. Orientation Analysis

Hand coding using the data obtained from the 14 daily living tasks was undertaken to determine the orientation of sensors using accelerometers only and is displayed in Table 2.

Table 2. Orientation of sensors with respect to gravity

	Device 1			Device 3			Device 4			Device 5		
Activity	Ax	Ay	Az	Ax	Ay	Az	Ax	Ay	Az	Ax	Ay	Az
1	0	1	0	0	0.5	-1	0	-1	0	0	-1	0
2	-0.5	1	-0.5	-0.5	0	-1	0	-1	0	0	-1	0
3	-1	0	-0.5	-0.5	-0.5	-1	0	-1	0	0	-1	0
4	1	0	0	-0.5	0.5	-1	0	-1	0	0	-1	0
5	0	-1	-0.25	0.25	-1	0	0	-1	0	0	-1	0
6	-0.5	1	-0.5	0	0.5	-1	0	-1	0	-0.5	-0.2	-0.75
7	-0.5	0.5	-1	0	0	-1	0	-1	0	-0.5	-0.2	-0.75
8	-1	0.5	-1	0.25	0	-1	0	-1	0	-0.5	-0.2	-0.75
9	1	0	0	-0.5	0.5	-1	0	-1	0	-0.5	-0.2	-0.75
10	0	-0.25	1	-0.25	-0.5	-1	0	-1	0	-0.5	-0.2	-0.75
11	0.5	1	0	-0.75	0.2	-0.5	-1	0	0	-0.75	0	-0.5
12	0	1	0	0	1	-0.5	-1	0	0	-0.75	0	-0.5
13	0.5	-1	0	-0.5	1	0	-1	0	0	-0.75	0	-0.5
14	-0.25	0	1	-0.25	0.5	0.75	-1	0	0	-0.75	0	-0.5

The developed processing algorithms were tested on each of the 14 tasks to look at correct classification and misclassification and are displayed in the Table 3.

Table 3. Task classification matrix

Trial number		Task Number															
	(n)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Sum
1	10	90	0	0	0	0	0	0	0	0	0	0	0	0	0	10	100
2	10	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	100
3	11	0	0	91	0	9	0	0	0	0	0	0	0	0	0	0	100
4	20	0	0	0	80	0	0	0	0	0	0	0	0	0	0	20	100
5	10	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	100
6	9	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	100
7	10	0	0	0	0	0	0	80	0	0	0	0	0	0	0	20	100
8	10	0	0	0	0	0	0	0	90	0	0	0	0	0	0	10	100
9	19	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	100
10	20	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	100
11	12	0	0	0	0	0	0	0	0	0	0	75	0	8	17	0	100
12	12	0	0	0	0	0	0	0	0	0	0	0	75	17	8	0	100
13	9	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	100
14	43	0	0	0	0	0	0	0	0	0	0	5	0	42	53	0	100
15	16	0	0	0	13	6	0	0	0	6	0	0	0	0	0	0	25

4. Conclusions

This paper sought to apply high performance sports inertial sensors into the classification and characterisation of fourteen activities of daily living. As such, these inertial sensors were intended as a proxy for traditional physical activity classification methodologies, such as recall questionnaires (e.g. Godin Leisure-Time Exercise Questionnaire), video capture motion analysis, or wired limb sensors frequently used in clinical biomechanics (e.g. “Flock of Birds”, Ascension Technology Corporation, USA). Each of the foregoing methods has certain drawbacks for routine physical activity quantification during the wakeful day of an individual in the “free-living” community-based environment.

We proposed inertial sensors could correctly quantify common daily movements and a specific health-related activity was devised to test the efficacy of the sensors to do so. In this application the determination of time spent in particular activities was the required metric. Using computationally simple algorithms’, classification was shown to be over 80% accurate for single individual performing patterned tasks.

There are several advantages for deploying inertial sensors to quantify leisure time physical activities in both healthy and clinical populations. These include: (1) such sensors are ‘real-time’ and do not require memory recall over a single days or days, (2) inertial sensors are neither wired nor cumbersome to be worn under clothing, and, (3) small sensors allow physical activity quantification outside of a laboratory environment sans retro-reflective or other body markers common in video capture motion analysis. A future advantage is that such sensors and appropriate software may be used to determine both the physical activity intensity and limb accelerations thereby replacing body-worn heart rate monitors as a method to determine exercise intensity for cardiovascular health.

It is envisaged that the next stages will involve more through testing 'in the wild' with different clinical populations and embedding these routines into the sensors themselves to reduce storage demands over a wakeful day.

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