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Dual Kalman filter for estimating load-free human motion kinematic energy expenditure

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ABSTRACT

The need for measuring energy expenditure using non-wearable devices in sports science is a complex task involving strict protocols of measurement. Such protocols and measurement involving indirect calorimetry or inertial measurement unit (IMU) based measurement are expensive to setup, too inaccurate or force the subjects being measured to modify their actions in a significant manner. In this paper, we explored the concept of using a parallel Kalman filter setup being used in simulation. The simulation used was an iterative one using a dynamic model, featuring the use of two different types of setup- structured or non structured movement and the use of one or two Kalman filters. The results from the simulations performed showed that structured movement using a dual Kalman filter setup was the best performer when using root mean square error as the metric for performance. These results will help influence our work utilising the Microsoft Kinect and estimating weights of human joints and the energy expenditure attained from that.

1. Introduction

In the world of sports, measuring an athlete's energy expenditure doing their general routine and practices for competition. This means that a measurement of an athlete's energy expenditure needed. These measurements are collected by equipping a V_{O_2} gas mask for indirect calorimetry based measurement is required. However this not only brings in a huge amount of cost, setting up time and the unwanted effects of loading the subjects body with external loads that are unusual for their activity. Another way was to introduce tracking movement with a Microsoft Kinect, where it has an in built algorithm for tracking the human body. However, the Kinect cannot track dynamic weights and the changes that occur whilst doing an exercise. To track these weight changes and correct them, we simulated limbs of subjects where they used a combination of structure and non-structured movements using a system consisting of either a single or dual Kalman filter. The results from these simulations were studied using multiple trial points and compared using root mean square error.

Ainslie et al. [1] reviewed approaches to estimate human energy expenditure. The different types of energy expenditure covered of note were the use of inertial measurement units and heart rate monitoring (HR). IMUs contain accelerometers, gyroscopes and magnetometers which measure linear acceleration, angular velocity and heading relative to the earth's magnetic field respectively. Heart rate monitors were found to measure total energy expenditure but could do so with an accuracy of 70%.

Work involving IMUs and estimating total energy expenditure was done on treadmills with a seemingly strong correlation of speed of ambulation, height and weight making an impact to the energy expenditure when referenced with a V_{O_2} gas mask measurement device [2]. Triaxial accelerometers were used to measure the velocity of a person's walk and total energy expenditure [3].

Meamarbashi et al. [4] estimated the exercise intensity by comparing different instrumental methods, including a PAMS data logger, a Suunto heart rate monitor and a three-axis pedometer, during walking and running in the field. In the experiment, ten male subjects were recruited and performed walking and running exercises with different speeds. By employing a linear regression, the relationship between the *XYZ* count of the PAMS data logger and MET estimated from ACSM equation was found. As a result, the Pearson correlation between MET computed from ACSE equation and PAMS was higher (0.968) than pedometer and Sunnto (both are

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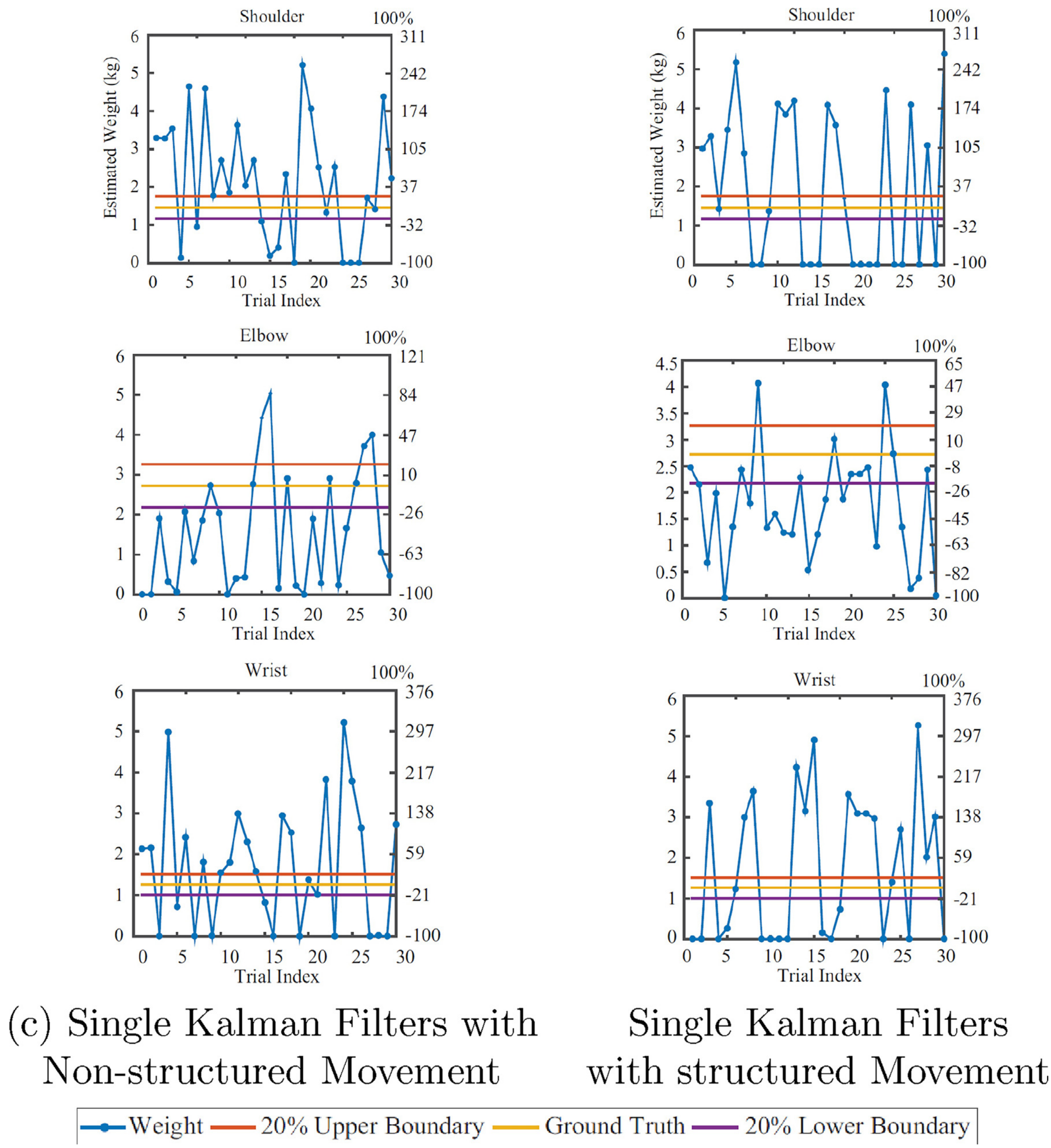

Fig. 1. Results of the simulation using only one Kalman filter.

0.937). At the same time, PAMS had shown the high reproducibility and validity in different speeds.

Kim et al. [5] proposed to utilise the acceleration and joint position calculated and collected from a Kinect to train a regression model with Support Vector Regression (SVR). Simultaneously, acceleration data was also collected from a accelerometer for comparison. As a ground truth, the Cosmed K4b2 portable gas analysis system was used to collect EE in Metabolic Equivalent of Task (MET). Two male subjects were involved in the related experiment to perform various motions, including light and vigorous activities. Therefore, two regression models were trained for each type of motions. For motion acceleration and spatial data, principle component was used to avoid over-fitting, and for the latter, a view-invariant representation scheme named joint-location-binning, was employed. Eventually, they reported that by using Kinect, the MET's predicted were within 17% of the ground truth for light activity and within 7% for vigorous, where accelerometers overestimate METs with 24% for the light and underestimate METs with 28% for vigorous activity.

Liu et al. [6] proposed an approach to estimate the energy expenditure during playing games by utilising the skeleton tracked by a Kinect. In their model, each motion was decomposed into vertical and horizontal plane. Energy expenditure of ith = [1, 2, . . ., 10] moving body part with mass of m_i in the former plane between frame t and $t+1$ was computed as $E_v(i) = m_i g \delta h_t$ where δt was the change of height on z axis. For the motion component on horizontal plane, $E_h(i) = E_x(i) + E_y(i)$, which were computed with the aid of movement speed and mass of each part. However, this paper did not give the accuracy of the estimation. Other studies did similar studies with a Kinect [7] with the subjects being tracked by a Kinect and gold standard VICON cameras whilst doing an exercise based game that involved five different games, many of them exercises related to self-stability and swaying.