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USE OF INFRARED SENSORS FOR ESTIMATION OF ENERGY EXPENDITURE BY ELDERLY PEOPLE LIVING ALONE AT HOME

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Abstract: Tri-axial accelerometers (triax) can estimate energy expenditure with a correlation of approximately 0.9. We explored the idea of developing an alternative non-contact method to estimate energy expenditure. In this paper, we present a statistical analysis of infrared sensor data and tri-axial accelerometer data to investigate a relationship between the infrared sensor outputs and energy expenditure as estimated using a triaxial accelerometer. Parametric regression of triax data and sensor data did not show any global fitting parameters. Non parametric regression method of locally weighted scatter plot smoothing (lowess) using tri-cube kernel weights gives an underlying trend of energy estimate. As it is a non-parametric method, it does not give us any global parameters to estimate measure of energy expenditure. But it gives us a good visual assessment of relationship between motion sensor data and accelerometer data.

I. Introduction

Population aging is progressing rapidly in Australia and other developed countries. [1, 2]. The dramatic increase in older population relative to the shrinking working population will overburden the social support system and health care services. Therefore, the focus of providing health care services to the aging population is shifting from the hospitals and aged care institutes to the home[3]. The long-term elder care responsibility of informal caregivers has increased their physical and emotional stress and financial burden. There is an urgent need to develop new technologies to reduce burdens on the informal caregiver and provide good quality of life to elders in their own homes [4-6]. The unobtrusive occupancy monitoring system has been developed by the Biomedical System Laboratory at the University of New South Wales, Australia for in-home monitoring of elderly people living alone in their home. The unobtrusive occupancy monitoring system consists of a transmitter and a receiver unit. The transmitter unit comprises a passive infrared motion sensor, a microcontroller and a ZigBee transceiver. Simplicity, Low power and low cost of monitoring system are the motivating factors for the choice of motion sensor and ZigBee wireless technology in the unobtrusive monitoring system. The motion sensor data sampled at 20 Hz is digitized by the12 bit analog to digital converter of the microcontroller. The digitized data is then subject to a motion detection algorithm embedded in the flash memory of the microcontroller. When the motion is detected, the digitized data is sent to the receiver unit wirelessly. The receiver unit's transceiver sends this data to local microcontroller for retrieval and forwards it to the computer base station via RS232 transceiver and a serial port.

II. Experimental Arrangement

The experiment for the energy expenditure estimate was performed in an air-conditioned room of size 7mx7m. Four transmitter units, each mounted on a tripod stand at a height of 2.1 m was placed at four corners of the room. The passive infrared sensor used in the transmitter unit was an analogue type sensor and had quad infrared sensor elements with a transparent Fresnel lens and an integrated amplifier. The sensor was designed to cover 110^0 horizontally and 93^0 vertically at 10meter radius. The receiver unit was connected via RS232 to the serial port of the computer.

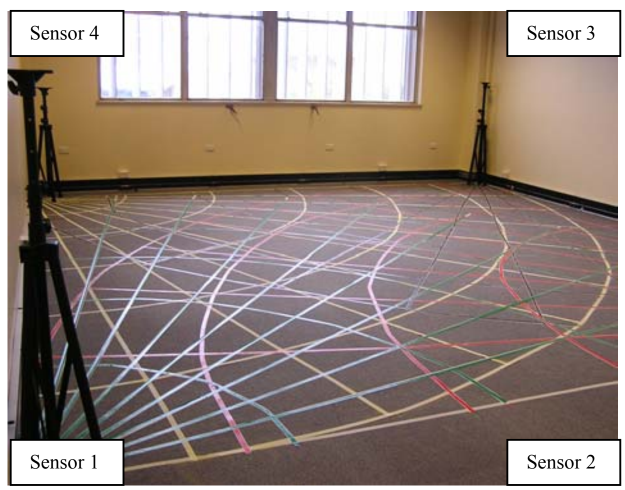


Figure 1: Experimental Arrangement (sensor 2 is not visible in the picture)

For the geometry of the path, the arcs were marked at a distance of 1m, 2m, 3m …etc. and radial lines were marked at a angle of 10^0, 20^0, 30^0 …etc. from the PIR sensor on the floor for each sensor as shown in fig.1. To estimate the energy expenditure by an occupant, we used a tri-axial accelerometer (triax) as a reference. The subject, wearing a triax, walked through the geometry marked on the floor at a speed of 0.4m/second (slow speed)

III. Results

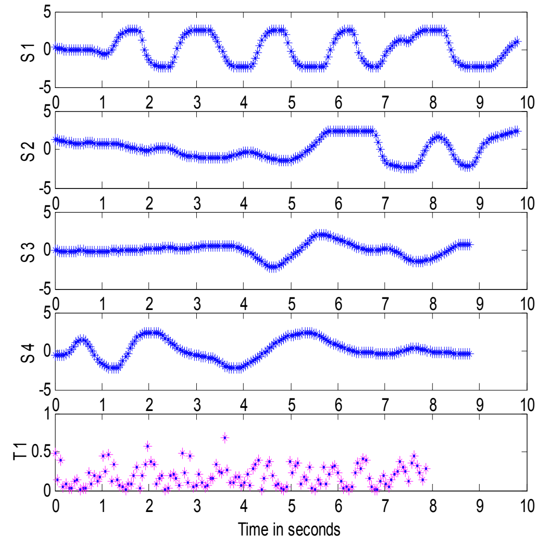
Literature shows that the energy expenditure is related to the acceleration signal, with around 90 % correlation [7] , by (1)

$$EE = \alpha IA = \alpha\left(\int |a1|\,dt + \int |a2|\,dt + \int |a3|\,dt\right) \qquad (1)$$

Where IA =integral area under each ac component of accelerometer output signal
α = constant of proportionality

The sample output signals from the four motion sensors and the energy expenditure estimated from the triax output is shown in fig.2 when the subject walked through arc 3 of sensor 1. We tested the hypotheses that the energy expenditure could be estimated from a linear or non-linear combination of outputs of the four PIR sensors using the triax energy estimate as a reference. It was taken care that there is synchronization in data collected from triax and the motion sensors. For energy expenditure calculations from the sensor data, no prior knowledge of location of the person in the room is available. The output of each PIR sensor must therefore be transformed identically and be equally weighted.

There is also no prior knowledge of what kind of relationship to expect between motion sensor output and triax energy estimate, different models are explored to estimate energy expenditure from the sensor data.



S1, S2, S3 and S4 = sensor 1,2,3,and 4 output voltage (raw)
T1= energy expenditure estimated from triax output

Figure 2: Output signal from the four sensors and energy expenditure estimated from the triax output

Dependent variable : Triax data	Model 1			Model 2			Model 3			Model 4		
	Coeff.	std.error	t value	Coeff.	std.error	t value	Coeff.	std.error	t value	Coeff.	std.error	t value
constant	0.33	0.02	22.05	0.35	0.02	15.31	0.35	0.02	15.32	0.33	0.01	23.16
Sensor data	-0.01	0.00	-1.90	-0.01	0.01	-1.93	-0.19	0.10	-1.94	-0.02	0.01	-1.63
Residual std.error		0.19			0.19			0.19			0.19	
R-Squared		0.01			0.03			0.03			0.04	
F statistics		3.605 on 1and 998 degrees of freedom			3.71 on 1 and 999 degree of freedom			3.759 on 1and 999 degree of freedom			2.651 on 1 and 998 degrees of freedom	
p value		0.05791			0.054			0.053			0.104	

Table 1: Statistical analysis of linear and non linear model

Model 1: $y = \beta_0 + \beta_1\ x + e$; where x =|x1|+|x2|+|x3|+|x4|
Model2: $y = \beta_0 + \beta_1\ x + e$; where x =sqrt |x1|+sqrt |x2|+sqrt |x3|+sqrt |x4|
Model 3: $y = \beta_0 + \beta_1\ x + e$; where x = |x1|^2+ |x2|^2+ |x3|^2+ |x4|^2
Model 4: $y = \beta_0 + \beta_1\ x + e$; where x=log (|x1|+|x2|+|x3|+|x4|)

The general equation between sensor data and triax data can be written [8] as given by (2)

$$y = f(x\ldots) + e \qquad (2)$$

Where f = unknown regression function
x= independent variables (sensor data)
y = dependent or response variable (triax data)
e = observation error

The motion sensors output and triax data is normalized on the same time scale for the purpose of parametric and non-parametric regression. The scatter plot between rectified sensor outputs in volts and energy expenditure estimated from triax output is shown in figure 3.

Linear or Non-Linear Models

The regression function can be a linear, non-linear or non-parametric. To start with we explored linear and nonlinear relationship. The independent variable x for linear and non-linear model is related to dependent data by (3)

$$y = \beta_0 + \beta_1 x + e \qquad (3)$$

where β_0 and β_1 are the regression coefficients and

$$x = f(x1, x2, x3, x4) \qquad (4)$$

x1, x2, x3 and x4 represents the absolute value of output of the sensor 1, 2, 3 and 4 respectively.

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Different linear and non- linear models were investigated and the results are shown in table (1). We calculated the best-fitting line for the observed data by minimizing the sum of the squares of the vertical deviations from each data point to the line. The coefficient of correlation (R squared value) for these models indicates there is no linear and non-linear relationship between motion sensor data and energy expenditure calculated from triax data.

Non-parametric models

The non-parametric regression analysis relaxes the assumption of linearity and helps us to explore the data visually, uncovering structure in the data that might otherwise be missed. The non parametric model can be represented as given by (5),

$$y_i = f(x_i) + e_i \qquad (5)$$

Where y_i is the ith response value
x_i is the ith predictor value
f is some smooth function
e_i are zero mean uncorrelated errors with a common variance

The models investigated are locally weighted scatter plot smoothing (loess), smoothing splines and general additive model. In loess model, a window of suitable width encloses the closest neighbors to each data observation. This window moves continuously over the data set, averaging the observations that are in the window and joins them together [9, 10]. The selection of window width is an important parameter in the non parametric regression.

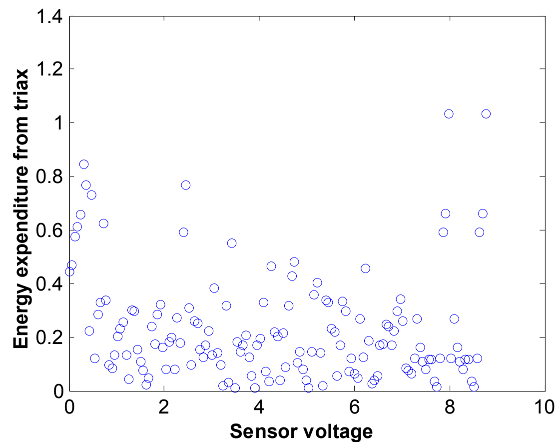

Figure 3: Scatter plot showing rectified sensor outputs in volts and energy expenditure estimated from triax output

The selection of window width is a trade off between bias and variance. The half window width called span for the loess model has been selected through the visual trial and error. We chose the smallest span (s =0.22) that provided a smoothest fit Different types of windows called the kernel estimator can be used to obtain the fitted values such as normal, tri-cube, rectangular or Gaussian kernel estimator. We chose tri-cube kernel estimator given by (6),

$$K(z) = \begin{cases} (1-|z|^3)^3 & \text{for } |z| < 1 \\ = 0 & \text{for } |z| \geq 1 \end{cases} \qquad (6)$$

The fitted curves of loess and kernel models are shown in fig.4

In the local polynomial regression instead of using equal weights as in ordinary least square, weighted least square regression the fits the equation (7)

$$Y_k = \beta_0 + \beta_1(x_i - x_0) + \beta_2(x_i - x_0)^2 + \ldots\ldots + \beta_k(x_i - x_0)^k + e_i \qquad (7)$$

In polynomial regression, models with different degree of polynomial are explored and summary of the model in shown in fig.4

The smoothing splines are piecewise polynomial functions that are joined at points called knots. The output of the models based on the natural and cubic splines are shown in fig 4. The nonparametric regression becomes quite complex if the predictors are more than 3. To make the analysis simple, the value of x used in regression is given by (8)

$$x = |x1| + |x2| + |x3| + |x4| \qquad (8)$$

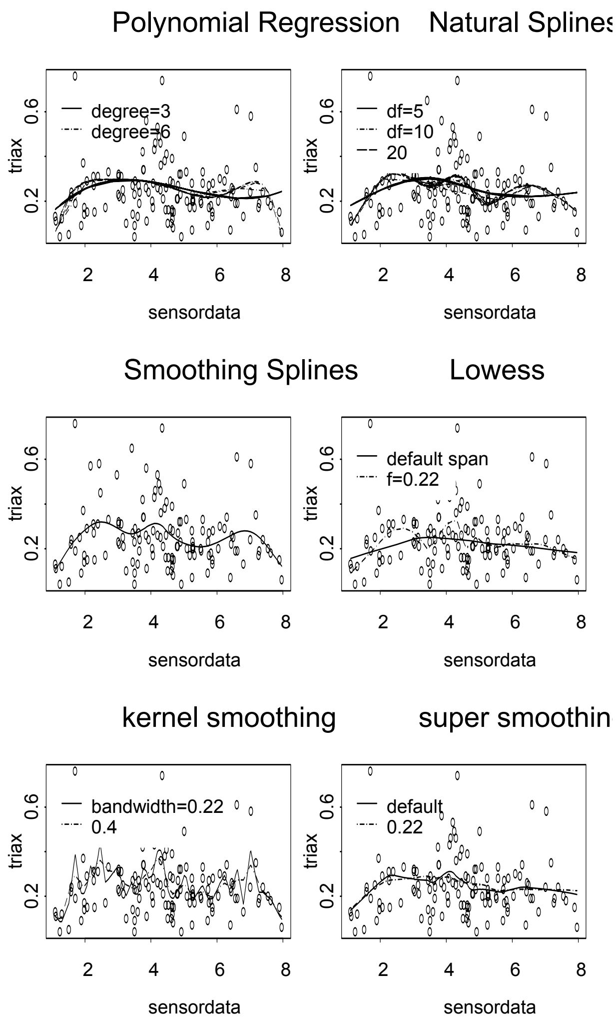

Figure 4: output of different nonparametric models

IV. Conclusion

The scatter plot in figure 3 shows no relationship between a subset of accelerometer data and sensor data. Linear and non-linear regression models justified this observation and coefficient of correlation did not show any pattern that may exit within limited subset of the data.

The nonparametric models enable us to describe the shape of the relation between triax data and sensor data without making restrictive hypothesis on the shape of the relation. The smooth curve for the Lowess model with tri cube weight kernel gives us quite a reasonable trend of variation of accelerometer data with least value for sum of squared error. The major limitation of non parametric smoothers is that they cannot be used to characterize the data in terms of a simple equation. As a result we conclude that energy expenditure cannot be adequately estimated from any linear and non-linear function we investigated. Non-parametric regression using kernel estimator with a bandwidth of 0.22 provided the best visual assessment of relationship between energy expenditure and sensor data.

References:

[1] AIHW 2002. Older Australia at a glance 2002 and Australian Institute of Health and Welfare, Older Australia at a Glance,3rd edition. 2002, AIHW Cat. No. AGE 25.Canberra: AIHW & Department of Health and Ageing.

[2] Aging in Australia, ACT Community and Health Services, in *Aging in Australia*. 2004, Aged and Community Services Australia.

[3] Camarinha Matos LM and Afsarmanesh H. *Design of Virtual Community Infrastructure for Elderly Care*. in *3rd IFIP Working Conference on Infrastructurees for Virtual Enterprises*. 2002.

[4] Johnson, Remote continuous physiological monitoring in the home. *Journal of Telemedicine and Telecare*, 1996. **2**: p. 107-13.

[5] Dutta Roy, Networks for Homes. *IEEE Spectrum*, December 1999. **36**: p. 26-33.

[6] Korhonen I, Pakka J, and Gils M v, Health Monitoring in the Home of Future. *IEEE Engineering in Medicine and Biology Magzine*, 2003. **22**(3): p. 66-73.

[7] M.J.Mathie, N.H.Lovell, A.C.F. Coster, and B.G.Celler. *Determining Activity using a triaxial Accelerometer*. in *2nd Joint EMBS-BMES Conference*. 2002. Houston, USA.

[8] R Lyman Ott and Micheal Longnecker, *An Introduction to the Statistical Methods and Data Analysis*. 5th edition ed. 2001: Thompson Learning, USA.

[9] Cleveland WS and Devlin SJ, Locally Weighted Regression: An Approach to regression analysis by local fitting. *Journal of American Statistical Association*, 1988. **83**(596-610).

[10] Fox J, *Multiple and Generalized Nonparametric Regression*. 2000: SAGE Publications.