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The urban brain: analysing outdoor physical activity with mobile EEG

Peter Aspinall,[1] Panagiotis Mavros,[2,3] Richard Coyne,[2] Jenny Roe[1]

[1]School of Built Environment, Heriot-Watt University, Edinburgh, UK
[2]Edinburgh School of Architecture and Landscape Architecture, The University of Edinburgh, Edinburgh, UK
[3]Center for Advanced Spatial Analysis, The Bartlett, UCL, London, UK

Correspondence to
Dr Jenny Roe, School of Built Environment, Heriot-Watt University, Riccarton, Edinburgh EH14 4AS, UK; j.roe@hw.ac.uk

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ABSTRACT

Background Researchers in environmental psychology, health studies and urban design are interested in the relationship between the environment, behaviour settings and emotions. In particular, happiness, or the presence of positive emotional mindsets, broadens an individual's thought-action repertoire with positive benefits to physical and intellectual activities, and to social and psychological resources. This occurs through play, exploration or similar activities. In addition, a body of restorative literature focuses on the potential benefits to emotional recovery from stress offered by green space and 'soft fascination'. However, access to the cortical correlates of emotional states of a person actively engaged within an environment has not been possible until recently. This study investigates the use of mobile electroencephalography (EEG) as a method to record and analyse the emotional experience of a group of walkers in three types of urban environment including a green space setting.

Methods Using Emotiv EPOC, a low-cost mobile EEG recorder, participants took part in a 25 min walk through three different areas of Edinburgh. The areas (of approximately equal length) were labelled zone 1 (urban shopping street), zone 2 (path through green space) and zone 3 (street in a busy commercial district). The equipment provided continuous recordings from five channels, labelled excitement (short-term), frustration, engagement, long-term excitement (or arousal) and meditation.

Results A new form of high-dimensional correlated component logistic regression analysis showed evidence of lower frustration, engagement and arousal, and higher meditation when moving into the green space zone; and higher engagement when moving out of it.

Conclusions Systematic differences in EEG recordings were found between three urban areas in line with restoration theory. This has implications for promoting urban green space as a mood-enhancing environment for walking or for other forms of physical or reflective activity.

BACKGROUND

Within environmental psychology, positive emotional mindsets[1] and specifically restorative theory[2 3] have proposed that natural settings promote recovery from stress and fatigue via attention restoration mechanisms. Soft fascination (intriguing environmental stimuli) promotes involuntary attention, enabling cognitive recovery from fatigue, and is typically present in natural settings. By contrast, hard fascination (demanding stimulation) grabs attention dramatically, increasing cognitive load, and is typically present in urban settings. The recovery from stress has been assessed in many different ways, including positive effects on heart rate,[3] perceived stress[4 5] and salivary cortisol.[6]

Brain studies are increasingly relevant as the development of affective computing[7] and brain–computer interfaces (BCI) enable researchers and designers to measure brain activity in environmental settings.[8] Although functional brain imaging has been used for subjects viewing environmental scenes in a laboratory setting,[9] no field data are available to our knowledge.

AIMS

Our study was aimed at exploring ways of using electroencephalography (EEG) technology in the assessment of urban experience.

There are two research questions.

1. Can the emotional impact of different urban environments be detected by cortical EEG signals while participants are walking through them?
2. Is there any evidence that urban green space can modify EEG signals in a restorative way, that is, reduction of stress, arousal and frustration and increase in meditation?

METHODS

Equipment

The Emotiv EPOC wireless EEG headset and accompanying software[10] was used for our research. EPOC consists of 14 sensors positioned on the wearer's scalp according to the international 10–20 system: antero-frontal (AF3, AF4, F3, F4, F7, F8), fronto-central (FC5, FC6), occipital (O1, O2), parietal (P7, P8) and temporal sites (T7, T8). Brain waves are measured in terms of amplitude (10–100 microvolts) and frequency (1–80 Hz). The four main independent bands are: δ (0.5–4 Hz), indicating deep sleep, restfulness, and conversely excitement or agitation when delta waves are suppressed; θ (4–8 Hz), indicating deep meditative states, daydreaming and automatic tasks; α (8–15 Hz), indicating relaxed alertness, restful and meditative states; β (15–30 Hz), indicating wakefulness, alertness, mental engagement and conscious processing of information. EPOC also includes a two-axis gyroscope to detect the wearer's head motion and orientation.

Emotiv EPOC is a novel, commercial device shifting from the medical EEG paradigm to affordable devices for commercial BCI use. Typical output from the device is shown in figure 1.

We do not have direct access to the manufacturer's algorithm relating to emotional parameters to raw EEG output on intellectual property rights (IPR) grounds. However, a number of studies have confirmed the reliability and validity of Emotiv's EEG performance[10 11] and the detection of emotional states.[12]

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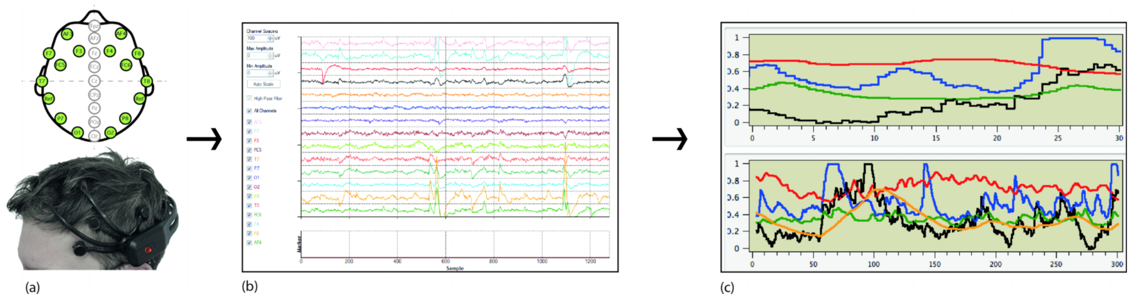

Figure 1 (A) Neural cap; (B) output from the Emotiv Testbench software: Emotiv EPOC records electroencephalography (EEG) signals from 14 sensor positions according to the 10–20 International System. Raw EEG signals are then 'translated' and classified in different emotional states and (C) output from the Emotiv Control Panel and 'Affectiv suite' (EEG data belong to the authors).

First, the EPOC EEG headset during feasibility trials[10] has been validated against a medical grade headset. The voltage and time resolution were found to be lower and the noise floor higher with the EPOC, but overall, the spectra and signals were regarded as well matched to a respected medical grade device. The amplifier linearity and channel phase differences were reported to be 'as good as any medical grade device—the resolution is limited only by the lower bit count and sampling rate'. Second, the validation of the headset has also been confirmed by a recent paper using the Emotiv mobile headgear in the *Journal of Psychophysiology*.[11] The paper concludes 'that good quality, single-trial EEG data suitable for mobile BCI can be obtained with affordable hardware'.

Our experiment involved a light, high-performing laptop with solid state storage, wireless EEG and a global positioning system (GPS) unit as shown in figure 2. For our experiments, we used Emotiv's 'Affectiv suite', which employs proprietary algorithms for filtering and translating combinations of EEG signals to four variables indicating emotional states, namely: excitement (long-term and short-term), frustration, engagement and meditation. We developed a custom-software platform to geoannotate emotional states from Emotiv's Affectiv suite in the conduct of our outdoor studies.

Participants

Twelve students from Edinburgh University were recruited to participate, and ethical scrutiny and approval for the study were provided by the School Ethics Committee. The mean age of the study participants was 30.08 with eight males, and four females.

The walk

The route was the same for all participants and it was selected to include three distinct zones in the centre of Edinburgh, of approximately equal length. These were zone 1 (urban shopping street with many people, 19th century buildings, light traffic); zone 2 (path through 26 ha green space, bordering lawns, playing fields with trees; and zone 3 (busy commercial district with heavy traffic, many pedestrians, high-noise levels). Photographs of the three zones are shown in figure 3A–C.

All of the 12 participating walkers travelled individually through the zones in the same sequence—zones 1, 2 and 3. The walkers were instructed to progress at their own pace and knew they were being observed by the researcher, who followed at a distance of 10–30 m.

All the walkers, except one, completed the walk within 24–26 min (mean 26.25 min, max 38.0 min). This generated around 48 000 lines of data (ie, around 4000 lines for each walker) across the five Emotiv channels. To reduce the volume of data, a 20% random sample was taken across all zones subsequent logistic regression analysis. This enabled two separate logistic regressions to be run with green space the common element. The consequence of this sampling resulted in

Figure 2 Diagram of the portable experimental gear. Emotiv EPOC's data (1) are geoannotated by a GPS unit and (2) stored on a laptop.

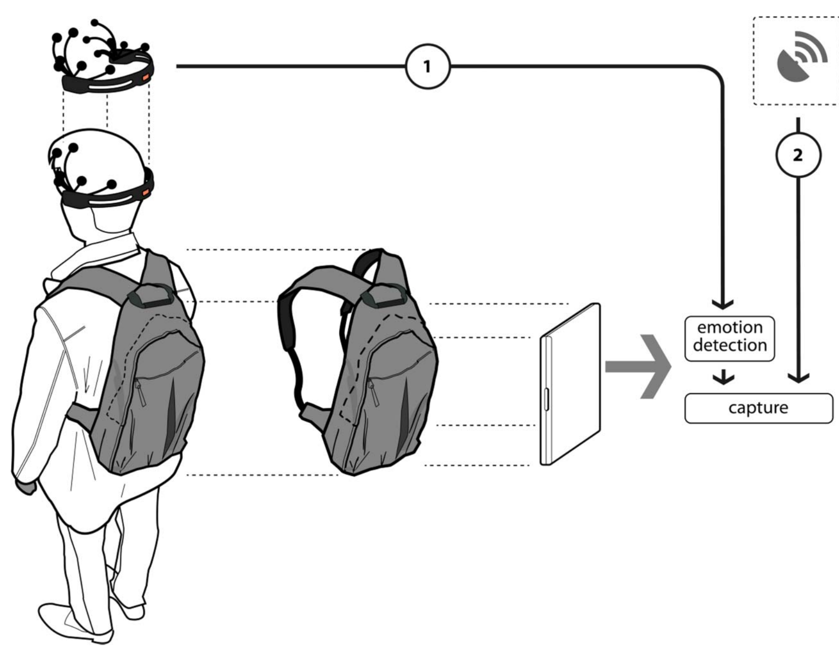

Figure 3 (A) Zone 1—urban shopping street; (B) zone 2—green space and (C) zone 3—busy commercial district.

approximately 800 records/person corresponding to around 5 min in walk duration.

Analysis

As traditional methods of regression are unsuitable for the form of data collected, which includes multiple records per case, a note is needed on the novel analysis used. We used a form of high dimensional correlated component regression analysis with M-fold cross-validation, which has a number of benefits in addition to its capacity to deal with multiple records and multicollinearity.[13 14] First, the usually recommended limits on the number of cases per predictor are relaxed to the extent that (p), the number or predictors, can exceed (n), the number of cases—hence, its definition as *high dimensional*. Second, the method's use of regularisation prevents model overfit and delivers improved out of sample prediction in M fold cross-validation.[14]

RESULTS

At a descriptive level, a map of the route and a typical EEG record from one participant are shown in figure 4A,B. The chart at the top of figure 4B shows the emotional levels from excitement (1) and frustration (2) while graph (3) shows long-term (LT) excitement levels that have been smoothed by Emotiv's software.

A record of the fluctuations in excitement and frustration is plotted as a map according to their geographical locale in figure 4B below. For example, this participant remains excited through zones 1 and 2, which are full of social interaction, whereas excitement falls in zone 3. Conversely, frustration

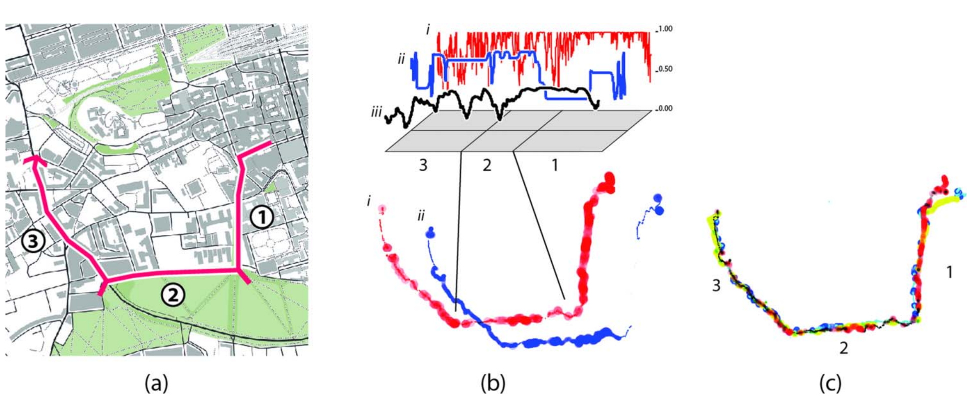

Figure 4 (A) Map of the route in central Edinburgh. (B) Emotional activity of one participant during the route, in charts (top of chart) and plot in space (bottom of chart). Red shows excitement; blue shows frustration. (C) Shows aggregate of excitement levels from the three participants. Peaks are in red, blue and yellow, respectively, for each participant.

Table 1 The accuracy of model fit; standardised β coefficients; and frequency of each predictor in 10 rounds of 10-fold (ie, 100) regression runs

	Training	Crossvalidation	SE
Fit			
R^2	0.0592	0.0579	0.0003
AUC	0.6441	0.6423	0.0006
Accuracy	0.6694	0.6678	0.0013

Standardised coefficients

Predictors	Standardised coefficient	1.2415 CC1	0.3264 CC2	0.0742 CC3
Frustration	−0.8756	−0.8663	0.7827	−0.7496
Engagement	−0.9007	−0.6649	−0.3232	0.4077
LT excitement	−0.1829	−0.0411	−0.3663	−0.1659
Meditation	0.3812	0.2380	0.2093	0.2351

Predictor table

Predictor	All	1	2	3	4	5	6	7	8	9	10
Frustration	100	10	10	10	10	10	10	10	10	10	10
Engagement	100	10	10	10	10	10	10	10	10	10	10
LT excitement	100	10	10	10	10	10	10	10	10	10	10
Meditation	100	10	10	10	10	10	10	10	10	10	10
Total	400	40	40	40	40	40	40	40	40	40	40
Predictors		4	4	4	4	4	4	4	4	4	4

All predictors were present in all runs.
AUC, area under the curve and LT excitement, long-term excitement.

seems to be highest at the start of the walk and lowest at the end. An aggregate visualisation of the excitement levels of three participants (figure 4C—peaks are in red, blue and yellow, respectively) reveals shared patterns of emotional activity, even though the experiment was performed on different days.

Comparison of zone 1 (urban shopping street) and zone 2 (green space)

The output from correlated component logistic regression analysis is shown in table 1.

At the top of table 1 under 'Fit' is the value of R^2 from crossvalidation together with its SE. Other rows of the table show the area under the curve and accuracy of the model prediction. Note that crossvalidation on out of sample prediction is close to the training value. The effect size from R squared is 0.058, which is at a small to medium level.[15]

Below 'Fit' is a table listing the usual regression output of standardised coefficients for each of the predictors. Table 1 shows that the rank order of standardised coefficients is engagement (ie, alertness), followed by frustration, meditation and LT excitement (or longer duration arousal). The negative sign indicates that the first zone is higher on the emotional measure than the second. In other words, in moving from zones 1 to 2 (from urban street to green space), the first three predictors in the table (ie, frustration, engagement or alertness and LT excitement) became lower, whereas meditation became higher.

To the right of the standardised coefficients of predictors are three columns of the correlated components (CC1, CC2 and CC3) showing the loading of each standardised coefficient across the components. The weighting of each component is given directly above it (eg, 1.2415, 0.3264 and 0.0742). In conventional regression, the number of components K is equal to the number of predictors p (ie, K=p=4 in this case). However, regularisation, which maximises R^2 while improving out of sample prediction, produces a three component solution. The graph in figure 5A is based on this three component solution and shows the red or darker line to be maximum for R squared at four predictors.

Finally, at the bottom of table 1, the predictor table gives the output of sample prediction across 100 regression runs (10 rounds each with 10 folds) within this case of four predictors present in all 100 regression runs.

Comparison of zone 2 (green space) and zone 3 (busy commercial district)

The results for this correlated component logistic regression are shown in table 2.

In the 'fit' table, the R squared value under crossvalidation is now 0.0203, which is considered small.[15] The standard coefficient table shows that there is just one predictor, which is engagement, and only one correlated component, CC1. This is confirmed by the graph in figure 5B in which the red or darker line for one component is maximum for R squared at one predictor. In this case, the sign of the predictor is positive, indicating that engagement or alertness is higher in zone 3, the busy commercial district.

Finally, the predictor table 2 shows that for out of sample predictions across 100 regressions (10 rounds each with 10-folds), one predictor (engagement) is present across all regression runs.

DISCUSSION

This study is one of the first to use a mobile EEG system outdoors and EEG-based emotion recognition software to record emotional changes as people walk through an urban

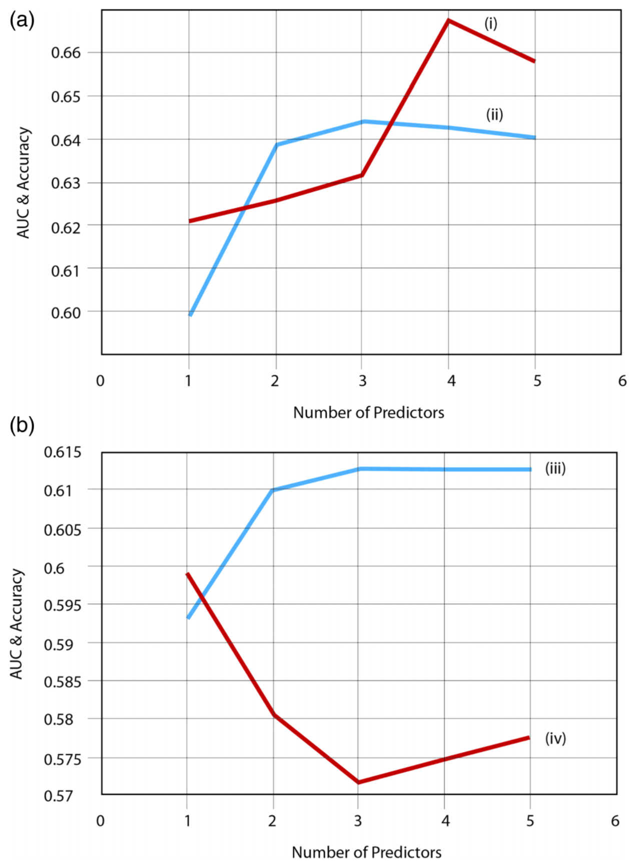

Figure 5 Graphs for area under the curve AUC (blue or light line) and cross validation accuracy (red or dark line) for the two logistic regressions. The latter is maximised at 4 predictors in (a) and 1 predictor in (b). (a) Showing the optimum four predictors for comparison zone 1 versus zone 2. (b) Showing the optimum single predictor for comparison zone 2 versus zone 3.

environment. Results confirm the research questions in showing systematic differences in processed EEG signals in different urban areas. The sequence of zones experienced was the same for all walkers. It is interesting to note that the transition from zone 1 to zone 2 (urban shopping street to green space) is in line with restorative theory with reductions in arousal, frustration, and engagement (ie, directed attention), and an increase in meditation. This change involves a greater range and subtlety of emotional response than the converse move from green space to busy commercial district (ie, heavy traffic/many people) in which one dimension of emotional change (engagement or alertness with directed attention) dominates.

In considering the limitations of the study, it would have been beneficial to have had access to the raw EEG measures, but this was not possible for the reasons given above. We also noticed that occasionally the EPOC was not streaming data, so we had to repeat the experiment or have a partial data set. In addition, owing to the ambulatory nature of the experiment, the trials produced data of varying quality with minor electrode displacements of the EPOC headset owing to the gait occasionally affecting the emotion detection algorithm.

Nonetheless, our findings are consistent with restorative theory and encourage the use of the technology to extend current research by developing novel and objective cortical correlates of emotion. This would be particularly beneficial in exploring the health improving potential of environments while people are on the move.

Contributors PA contributed to the research design and carried out data analysis. He was involved in the writing of the paper. PM contributed to the research design, recruited to the study, developed the technology, collected all data and supplied the visual images. RC contributed to the research design, interpretation of data and writing of the paper. JR inputted into the research design, supplied the restorative theory framework and the writing of the paper. We confirm that all the authors meet conditions 1, 2 and 3 below: (1) substantial contributions to the conception and design, acquisition of data, or analysis and interpretation of data; (2) drafting the article or revising it critically for important intellectual content and (3) final approval of the version to be published.

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Competing interests None.

Ethics approval The University of Edinburgh School of Arts, Culture and Environment Ethics Committee.

Provenance and peer review Not commissioned; externally peer reviewed.

Table 2 The same information for one predictor

	Training	Crossvalidation	SE
Fit			
R^2	0.0206	0.0203	0.0001
AUC	0.6119	0.5931	0.0012
Accuracy	0.5993	0.5992	0.0003

Standardised coefficients

Predictors	Standardised coefficient	0.7159 CC1
Engagement	0.7159	1.0000

Predictor table

Predictor	All	1	2	3	4	5	6	7	8	9	10
Engagement	100	10	10	10	10	10	10	10	10	10	10
Total	100	10	10	10	10	10	10	10	10	10	10
Predictors		1	1	1	1	1	1	1	1	1	1

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