ReRide: A Bike Area Network for Embodied Self-monitoring during Motorbike Commute.

Naveen L. Bagalkot
Gaurav Singh
Vineeta Rath
Srishti Institute of Art, Design, & Technology,
Bengaluru 560064, India
naveen@srishti.ac.in
gaurav.singh@srishti.ac.in
vineeta.rath@srishti.ac.in

Tomas Sokoler
IT University of Copenhagen
DK-2300 Copenhagen S
Denmark
sokoler@itu.dk

Anchit Shukla
Indian Institute of Technology
Roorkee, Roorkee - 247667
India
ashukla@ce.iitr.ac.in

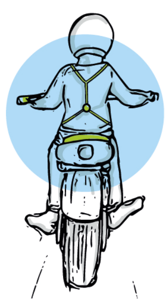
Abstract
Motorbike commuting is the new frontier for exploring digital technology where designing for embodied interaction takes on a more central role. In this paper, building on previous work on embodied self-monitoring, we present our ongoing work of designing a modular platform with a particular focus on real-time estimation and presentation of posture data while riding. In particular, we present 'Bike Area Network' (BANk) as a system architecture to help guide the design of such a platform. We share our ongoing work as an invitation for the community of researchers and practitioners of designing for embodied interaction to further explore this new frontier of research.

Author Keywords
Embodied Self-monitoring; Motorbike Riding; Real-time Posture detection; Personal Informatics.

CSS Concepts
• Human-centered computing~Interaction design theory, concepts and paradigms • Human-centered computing~Ubiquitous and mobile computing theory, concepts and paradigms • Human-centered computing~Ubiquitous and mobile computing design and evaluation methods

Pre Ride

Diva commutes to her work on her motorbike daily. She has been doing so for the past 5 years, and now is in the danger of developing repetitive strain injury of her lower back.



On Ride

She then starts using ReRide. ReRide consists of two parts:
a) A sensing system of multiple peripherals and b) a display unit that displays this information real-time, next to the motorbike's dashboard.

Figure 1: Use case scenarios of ReRide

Introduction

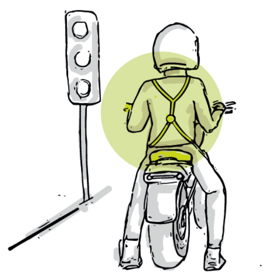
Taking embodied interaction [9,15] as the theoretical foundation our previous research, on the design of pervasive and mobile digital technologies for of out-of-clinic physical rehabilitation, has suggested the construct of 'embodied self-monitoring' [5,6]. Design for embodied self-monitoring aims to bring forward opportunities to help the rehabilitees integrate parts of a regimen for physical rehabilitation with everyday activities. Furthermore, it enables a more specific application of Lived Informatics in the situation of physical rehabilitation [2]. Having recognized the many similarities between out-of-clinic physical rehabilitation and doing physical exercise as part of preventive self-care, we ask if the design for embodied self-monitoring could guide design for preventive self-care? That is, if and how could digital technology be designed to bring forward opportunities for people to turn everyday activities into exercises for preventive self-care?

In our ongoing work, we take everyday motorbike commute through dense urban traffic as the everyday activity and explore through design if and how adding data on lower-back posture to the experience of riding would present opportunities for the rider to perform simple lower-back exercises during the ride? In particular, we look into the design of a system that, by offering the rider cues about their back posture seeks to enable and encourage bike riders to carry out preventive measures as an integrated part of riding.

Previously we have explored digital technology and embodied interaction in the context of motorbike riding, presenting an interactive sketch through which we explored and narrowed in on the kind of experience and interaction a system for real-time posture feedback should enable [4,14]. Subsequently, we designed and developed a software-hardware architecture for a platform enabling experiments around embodied self-monitoring [3]. From these experiences, we realized that we need a more modular system in order to experiment with the possibilities of supporting embodied self-monitoring in more depth, covering all the four scenarios of use (see figure 1 and 3).

In this paper, we present our ongoing work of designing a robust and modular platform, with a particular focus on real-time estimation and presentation of posture data while riding (to explore the 'On Ride' scenario in depth, refer figure 1 and 3). In particular, we present 'Bike Area Network' (BANk) as a system architecture to help guide the design of such a platform. Furthermore, we present the process of developing the software and hardware interactive prototype, including explorations of real-time posture detection and visualization for on-ride feedback.

Through sharing our ongoing and evolving work, we further the emerging discourse around specific use-cases of embodied self-monitoring, moving beyond physical rehabilitation and towards preventive self-care. In particular, our work makes the possibilities of in-situ experimentation towards designing for embodied self-monitoring in the specific context of motorbike commuting more real. Furthermore, through sharing our evolving process of designing the modular platform we invite the broad community of designers and researchers exploring embodied interaction to explore the exciting frontier of digital technologies for embodied self-monitoring in the context of motorbike commuting.



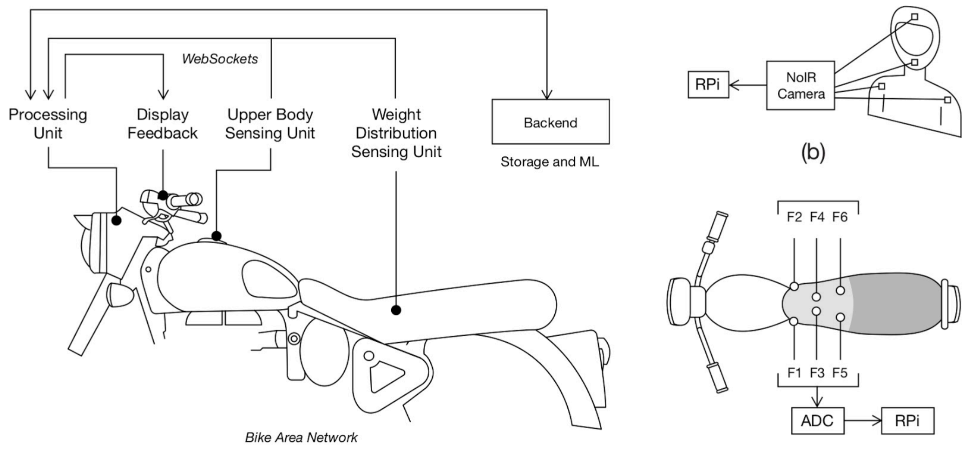
Pause during Ride

When she temporarily stops riding, she can see historical data about the present ride upto that moment.

Post Ride

Post completion of ride, she checks the detailed reports about her posture during her rides on her phone

Figure 3: Use case scenarios of ReRide.



(a) (b) (c)

Figure 2: System Architecture: (a) Bike Area Network, (b) Upper body tracking sensor unit, (c) Weight distribution sensing unit

BANk: A Modular System Architecture

We envision ReRide system as a PaaS (Platform as a Service), a modular system of hardware and software located on the bike and a cloud server. The Bike Area Network (BANk) forms the core architecture of the platform. We define BANk as a specialised local area network to wirelessly interface sensing modules to the processing module (also located on the bike), fetch rider data from the backend (at a remote location on cloud server), and display it on the rider dashboard (see figure 2). The central components of BANk are,

1. Sensing modules. Each sensing module is a combination of a sensor and a Raspberry Pi[1] unit.
2. A central processing module, consisting of a Raspberry Pi, which reads the data from sensing modules and publishes it to the remote server for later access or further processing through Machine Learning models. It is responsible for abstracting the raw information to relevant data that can be visualized by the display module.
3. Display module. In the current form this is a smartphone with a specific browser based visualization of rider data. But we imagine it to be integrated with the motorbike's digital dashboard.

In the current version, we use two sensing modules: (a) Weight distribution sensing module and (b) Upper-body sensing module. The aim is to enable us to estimate dynamic posture of the rider and suggest visual feedback to the rider through the display module.

[1] Raspberry Pi Zero W (Microcontroller board, 802.11b/g/n WLAN, 1GHz, single-core CPU, 512MB RAM, Micro USB power, Hat-compatible 40-pin header, CSI camera connector) https://www.raspberrypi.org/products/raspberry-pi-zero-w/

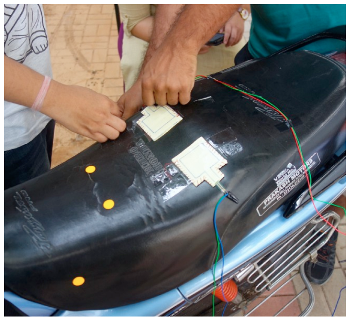


Figure 5: Fixing the FSR Matrix on the seat of the bike

Figure 6: Rig for camera sensor module mount on the motorbike.

Weight Distribution Sensing Module

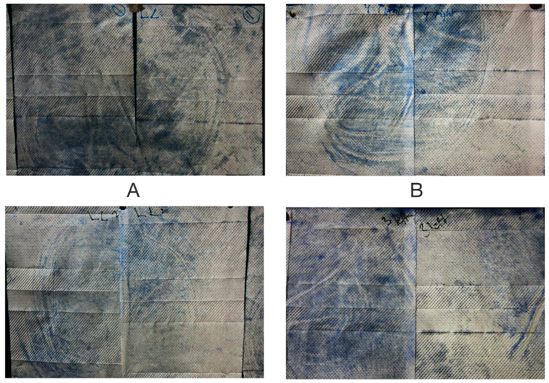


Figure 4: Pressure map transferred on tissue paper through Carbon paper; A-Forward Lean, B-Right Lean, C-Backward Lean, D-Left Lean

The weight distribution sensing module consists of a Raspberry Pi connected with a matrix of force sensitive resistors (FSR) [11,13] strapped on the motorbike seat (see figure 5). The matrix is arranged in a particular configuration to help us estimate the change in the weight distribution on the seat at different poses during the ride [1]. We determined the configuration the FSR matrix through multiple experiments that looked at how the rider's weight changes at different poses (see figure 4).

There are six FSRs which send analog signals to the connected Raspberry Pi on I2C (Inter-Integrated Circuit) interface through two 16-Bit/4-Channel Analog to Digital Converter Adafruit ADS1115 16-Bit/4 Channel ADC with Programmable Gain Amplifier[2]. The Raspberry Pi reads the FSR values and broadcasts them for the central processing module to read over WebSockets[3]. In particular, the front and middle FSRs enable us to determine if the rider is left or right, and along with the rear ones they together help us understand if the rider is leaning front or backward.

Upper-body Sensing Module

The upper-body sensing module consists of a Raspberry Pi connected with an 8MP NoIR camera[4] mounted near the bike dashboard facing the rider's upper body (see figure 6). The camera works at 30fps and is sufficient for recognizing specific ARuco markers [10] placed on the rider's helmet and shoulders under dim light. The markers are placed at specific points to extract rider's proximity from the camera, shoulder tilt, and head stoop. The attributes from the camera along with FSR data are used to extract several features of posture with reasonable confidence. The upper-body sensing module also sends these attribute data to the processing module over WebSockets.

Posture Estimation

The processing module evaluates data from the sensing modules and calculates the various relevant attributes that contribute to the dynamic posture of the rider. The evaluation helps in understanding rider's forward lean, shoulder tilt, head stoop, left or right lean. While the accurate understanding of posture requires precise scanning of critical joints in the body, ReRide system instead looks at the ways to determine the information that is sufficient to be suggestive. This data is used in creating the visual feedback for the user to make sense

[2] https://www.adafruit.com/product/1085

[3] (RFC 6455) https://tools.ietf.org/html/rfc6455

[4] Raspberry Pi NoIR Camera module v2 https://www.raspberrypi.org/products/pi-noir-camera-v2

as part of embodied self-monitoring across the use-scenarios (figure 1 and 3).

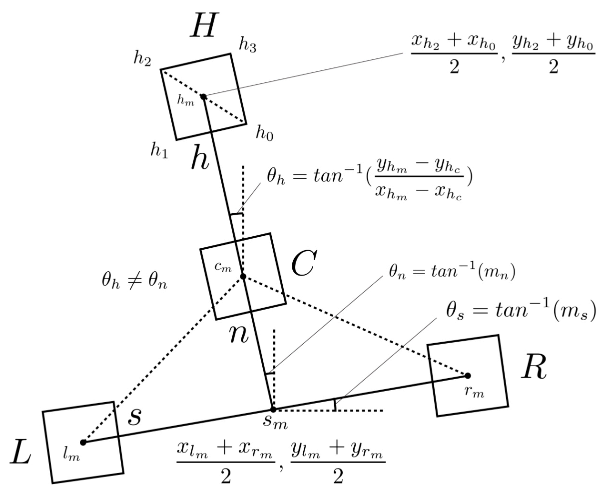


Figure 7: Marker configuration and extraction of relevant posture characteristics

Forward Lean is primarily calculated by estimating how close is the rider from the camera and the weight distribution on the seat. A reasonable confidence is achieved by combining inputs from both the sensing units. As figure 7 shows how the rider's proximity is estimated primarily by looking at the ratio of the size of the face to the height of the video frame. The size of the face is given by the distance from the mid-point of Head marker (H) to the mid-point of Chin marker (C). Other supporting data include the decrease in the area of the triangle formed by the mid-points of each C, Left Shoulder (L) and Right Shoulder (R) markers. In the weight distribution, the forward lean is indicated when there is a relative decrease in the weight exerted at the rear FSR patches.

Shoulder tilt is calculated by solely the camera unit. It is given by the slope of the line joined between the mid-points of L and R marker. The ***shoulder twist*** in this context is the movement of shoulders in the horizontal plane and can be given the ratio of the area of the L and R markers. ***Head stoop*** occurs when the head orientation does not match with spine inclination. While the forward lean parameter estimates a general inclination of the upper body of the rider, head stoop strictly measures the inclination of the head in the forward direction. Head stoop is also given by the ratio of the size of the face to the height of the video frame while the significantly lesser difference in the area of the triangle formed by the mid-points of each C, L and R markers. ***Head tilt*** is given by measuring the slope of the line between the mid-points of H and C marker to the vertical reference line of the video frame.

Left and Right lean is primarily given by the weight distribution unit. The indication is given by the significant difference between the FSR patches placed at under left and right thigh. A reasonable confidence is achieved by combining this data with the upper body tilt given by calculating the slope of the line between mid-point of C and the mid-point of L and R marker about the horizontal reference of the video frame.

Visual Feedback

The estimated posture is visualized for glanceable feedback [7] on the screen of the display module, through an amoeba-like blob (See figure 8). The extent of amoeba along different axes is computed by averaging posture characteristics as per current ride, current day, last day, last 3 days, last week and so on. These parameters are mapped on the axes that closely mimic the top view of the rider. The text labels in the

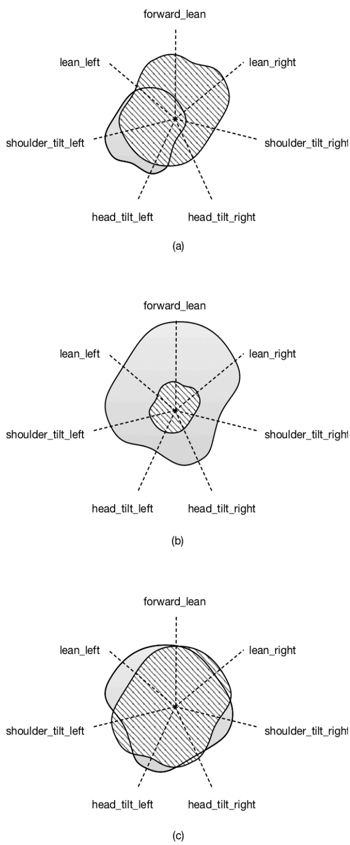


Figure 8: Typical visual feedback cases- (a) New or unlearned system, the suggested amoeba has significant non-intersecting area, (b) Experienced system but insignificant improvement in user, (c) Experienced system with significant improvement in user

figure are only for the purpose of annotation, the actual visualization uses symbolic signifiers. Over time, the signifiers may be eliminated as the rider would get familiar with the characteristics. The motivation for such a visualization is based on our previous explorations and the fact that a single instantaneous posture may not be regarded as good or bad, but the rider being in a particular posture for longer durations may be bad.

The visualization indicates a growing/shrinking amoeba along with another amoeba in a different fill color. The other amoeba is computed by the system to indicate user what may be right for the rider. This amoeba also grows and shrinks in real-time but more gradually based on the rider's history and medical profile through a LSTM (Long Short-Term Memory) network. We hope that over the time, the rider would try to change his posture to correct his amoeba visualization. The motivation to use the LSTM network [12] is the capability of learning long-term dependencies and sometimes avoid them. For instance, consider a case where the rider has the inherent inability to sit without leaning on one of his sides. The ReRide system is expected to learn and consider this inability and suggest accordingly.

Future Work & Concluding Remarks

We are in the process of integrating BANk and its modules presented here into a fully working prototype, mounted on a motorbike. As we have reached a firm foundation in terms of the overall structure of the system, we can now iterate on visualizations in detail with actual ride data, and develop a learning model (LSTM variant) for this context. These studies will help us not only to establish the viability of such a system in the real-world, but more importantly to continue experimenting on the diverse range of rider experiences of embodied self-monitoring across, and beyond the use scenarios (figure 1 and 3).

In more specific terms, the architecture facilitates us to conduct further research about postural data and its effect on the user. In the current version, we looked at developing a system to estimate rider's posture and giving them the real-time information about the same to support embodied self-monitoring towards preventive self-care. Our current work establishes that the platform mounted on the motorbike will enable us to conduct in-depth research about the ways in which riders perform embodied self-monitoring before, during and after the ride. It will enable us to also explore what roles do posture data and the way it is presented for rider engagement play in supporting embodied self-monitoring aimed at preventive self-care.

In this paper, we presented our ongoing work on designing and developing a robust and modular platform for enabling in-situ experiments towards designing for embodied self-monitoring during motorbike commuting. Building on previous work [3,4,14], we presented 'Bike Area Network' (BANk) as a system architecture to help guide the design of such a platform. Furthermore, we presented the process of developing the software and hardware interactive prototype, including explorations of real-time posture detection and visualization for on-ride feedback. We share our ongoing work as an invitation for researchers and practitioners of designing for embodied interaction to further explore a new frontier: Motorbike commuting.

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