Detecting and Visualizing Context and Stress via a Fuzzy Rule-Based System During Commuter Driving

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Abstract— **Stress is a negative emotion that occurs in everyday life, such as driving. Recurrent exposure to stress can be detrimental to cardiovascular health in the long term. Nevertheless, the development of adaptive coping strategies can mitigate the influence of everyday stress on cardiovascular health. Understanding context is essential to modelling the occurrence of stress and other negative emotions during everyday life. However, driving is a highly dynamic environment, whereby the context is often described using ambiguous linguistic terms, which can be difficult to quantify. This paper proposes a Fuzzy Logic Mamdani Model to automatically estimate different categories of driving context. The system is comprised of two Membership Functions (MFs), which converts the inputs of speed and traffic density into linguistic variables. Our approach then uses these data to identify six states of driving – Idling, Journey Impedance, High Urban Workload, Low Urban Workload, High Non-Urban Workload and Low Non-Urban Workload. An interactive visualization has then been implemented that links this fuzzy logic model with psychophysiological data to identify the context of stress experienced on the road. The system has been validated using real-world data that has been collected from eight participants during their daily commuter journeys.**

Keywords—Emotion Recognition; Mobile Health; Pervasive Computing; Physiological Computing; Stress; Wearable Computers; Fuzzy Logic; Negative Emotion

I. Introduction

Emotions are a powerful influence that can positively and negatively affect long-term health. Emotions can impact on health both indirectly (through changing behaviour) or directly (by altering the central nervous and cardiovascular systems) [1]. Negative emotions, such as stress and anger, are frequently experienced in daily life, but increased exposure can adversely affect cardiovascular health in the long-term. For instance, pro-inflammatory cytokines, including interleukin 6 (IL-6) and C-Reactive Proteins (CRP) are associated with anxiety and depression; this inflammatory process can exacerbate cardiovascular disease (CVD), certain cancers and osteoporosis [2]. CVD is a group of disorders of the heart, including coronary heart disease (CHD), and is the leading cause of death worldwide [3]. For instance, men who experience high hostility are more than twice at risk of cardiovascular mortality compared with those who experience low hostility (anger) [1]. Anger and stress are known risk factors for developing CHD and inflammation is a key biological marker of this process [4], [5].

Driving is a common every day activity undertaken by millions of people. The act of driving can be a stressful experience due to mental workload or negative encounters with other road users, which leads to negative emotional states. For example, aggression is more frequent on the road than in any other human setting, with complex traffic environments negatively affecting driver stress and performance [6], [7]. Traffic congestion leading to journey impedance is another known environmental stressor that is associated with low speed and high traffic density [8], [9]. This not only presents safety risks, as high anger drivers are twice as likely to crash in high impedance situations and are generally more angry, but also creates a situation that provokes negative emotions and inflammation [10]. The effect of inflammation on health may not be immediately obvious over a period of days, weeks or months. However, a lifetime of driving can have a significant negative impact on cardiovascular health. It is therefore important to understand the context of negative emotions experienced during driving to enable the development of adaptive coping strategies.

Associating fleeting moments of negative emotions with driving conditions is not a straightforward task, as driving conditions are highly dynamic and probabilistic. Furthermore, driving parameters, including speed and traffic density, are often described using linguistic terms, such as "slow", "average" or "fast". For example, a situation can be described in the following manner, "*There were a lot of cars around and so I was driving slowly*". The pattern of acceleration and deceleration of the vehicle can be described within a linguistic framework, which humans can describe and understand as being "*fast*", "*slow*" or "*not that fast/slow*." However, computing systems generally cannot process this type of input and instead process data as crisp binary inputs, either being "*fast*" or "*slow*" without an intermediate state. However, fuzzy logic can overcome this challenge by processing vague human language and mapping inputs/output onto linguistic descriptors [11]. Fuzzy logic allows data to fall into a range and assigns output variables based on its degree of membership, as opposed to the traditional "true" or "false" ("0" or "1") crisp outputs [11]. For instance, without fuzzy logic if we had a rule whereby "*fast*" was assigned to all data greater than 60 mph but a car was travelling at 59 mph this would be grouped within the "*slow*" category when it falls very close to the criterion to be labelled as "*fast*." Nevertheless, fuzzy logic allows us to assign a degree of membership to each data point (between 0 and 1) that characterizes group membership on a probabilistic continuum.

The current work investigates this approach by proposing a fuzzy rule-based system, which is based on smartphone data, to derive different categories of driving context. Using a previously established method [12], the high frequency (HF) measure of heart rate variability (HRV) was then used to label the

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psychophysiological dataset into "stressful" occurrences. These data were then linked to the categories of driving context that were derived from the fuzzy rule-based system and displayed as an interactive visualization. The purpose of this visualization was to understand the context of inflammation associated with stress that was experienced during each journey. Data has been collected from participants via our mobile platform during their normal daily commutes to and from work, thus increasing the ecological validity of the findings.

The reminder of this paper is constructed as follows. Section 2 describes related work in the areas of stress detection and detecting driver behaviour via fuzzy logic. Section 3 details the experimental protocol that has been undertaken. Section 4 describes the stress detection system that has been implemented. Finally, the paper is concluded, and the future directions of the research are presented in section 5.

II. Related Work

Sensors and smartphones have been extensively used across the healthcare sector to monitor various parameters, including heart rate (HR), heart rate variability (HRV), pulse, body temperature, etc., which can be used to quantify stress [13], [14]. HRV is a useful and non-invasive measure that provides unobtrusive information about the modulation of the heart rate by the autonomic nervous system [15]. When stress is triggered, HR increases, as part of the fight-or-flight response, whilst there is often an inverse relationship between perceived emotional stress and HRV [15]. For instance, Boateng and Kotz's [16] *StressAware* application uses real time HR and heart-rate variability (HRV) data from a commercial wearable heart-rate monitor to continuously monitor the stress levels of individuals. It was reported from the usability feedback that people enjoyed being notified about their stress level. In previous works, negative emotions have been measured during real-life driving through the development of a mobile lifelogging system [12], [17], [18]. This included developing a set of algorithms to process multiple streams of raw physiological data [18], as well as exploring an alternative approach to labelling data for machine learning [12]. This approach provided greater fidelity by using psychophysiological data (e.g. heart rate) to dynamically label data derived from the driving task (e.g. speed, road type). This paper is an extension of this previous work that focuses on developing a fuzzy rule-based system that can differentiate between different categories of driving context.

Fuzzy logic has been used within many research studies to model driving behaviour [19]–[22]. For instance, Feraud et al. [20] have used fuzzy logic to estimate safe driving behaviour based on speed traffic violations. The system collects data including the location (latitude/longitude coordinates) of traffic speed signs and vehicle data, including speed, location and time. Their model uses a Sugeno controller with two input variables – excess speed, which has been defined with the linguistic labels of "*low*", "*medium*" or "*high*" and severity of the traffic violation, which has been labelled as "*low*", "*moderate*" or "*severe*". Using these two inputs, the rules define the output estimation of the traffic violation that has occurred, which has been defined using three possible outcomes, "*high*", "*medium*" and "*low*". In other works, Wu et al. [22] have proposed a fuzzy logic model to monitor driving behaviour by recognizing certain activities, including normal driving, acceleration/deceleration, changing lanes, zigzag driving, and approaching the car in front. The output of their system is a score to estimate the drivers behaviour, which has been defined using three possible outcomes, "*high risk*", "*medium risk*" and "*low risk*".

Whilst these studies have explored driver behaviour in respect to driving violations, there has been little work that combines the fuzzy logic method with physiological measures to determine the triggers and context for stress.

III. Experiment Protocol

A. Participants

Real-world data were collected from eight participants – six females and two males, with an age range from 28 to 57 (mean age = 39.50 yrs., SD = 11.10 yrs.), on their daily commutes to and from their place of work. All participants were healthy and did not have a history of heart disease and were not currently taking any medication that could influence cardiovascular activity. The Liverpool John Moores University Ethical Committee has approved all procedures for participant recruitment and data collection prior to commencement of these studies.

B. Data Acquisition

Raw data was collected via our mobile data collection platform, which consisted of a smartphone and two wearable Shimmer3™ sensors that collected raw electrocardiograph (ECG) signals, via a 5-lead ECG unit, and photoplethysmogram (PPG) data, via an optical pulse ear-clip. The sensors were configured to a sample rate of 512 Hz. A Samsung™ Galaxy S5/S6 smartphone collected contextual data from the drive, including speed of the vehicle, location and photographs. Data was stored on the internal microSD card of each device. Participants were trained with the equipment for approximately 60 minutes before undertaking the studies.

Data was collected over five working days. To take part in the studies, drivers' normal commuter journeys had to include more than 10 minutes of continuous driving (per journey). Participants then had to 1) take the same route to and from work, at approximately the same time (per journey), 2) be alone in the car and 3) not listen to music. Please see previous work for a detailed description of the study [18]. The driving times ranged from 16:30 minutes – 01:48:30 hours (mean drive time = 37:22 min, SD = 20:06 min). This study resulted in the collection of 159,496,783 instances of raw data (~43 hours).

C. Experimental Measures

The raw ECG and PPG data were subjected to extensive pre-processing to identify and remove artefacts and to correct baseline wander. Details of this process have been described in [18]. Time domain measures were then calculated from the ECG/PPG data, including descriptive statistics of the IBI and PPI (average, standard deviation, median, minimum and maximum), as well as heart rate and the root mean square of differences of successive RR intervals (RMSSD). Frequency domain measures included total power (TP) of all intervals between 0 and 0.4 Hz per window, high frequency (HF) power between 0.15 and 0.4 Hz per window, low frequency (LF) power between 0.04 and 0.15 Hz per window, very low frequency power (VLF) between 0.0033 and 0.04 Hz per window and the ratio between low and high frequency (LF/HF). These are important as RMSSD, LF and HF are measures of heart rate variability [23].

Driving measures that were extracted from the smartphone included latitude and longitude coordinates (to derive location), speed (mph), distance travelled (m) and time of journey. Road measures were also extracted from the photographs. These included traffic density (count of moving cars in the lane(s) immediately ahead of the vehicle), road complexity (number of lanes), road type, weather, the presence of traffic lights (and their associated color), if the car is stopped or in slow moving traffic and if the car was at a roundabout.

IV. Fuzzy Stress Detection System

The system proposed in the current paper aims to detect driving context during real life driving, via fuzzy logic, and visualize this data via an interactive interface. Fig. 1 illustrates a high-level overview of the system. In order to implement the fuzzy system the following steps must be undertaken [11]:

1. *Fuzzification* – input data is converted into separate Membership Functions (MFs) using linguistic variables
2. *Fuzzy Inference Process* – membership functions are combined with rules to derive fuzzy outputs using a Mamdani model
3. *Defuzzification* – fuzzy outputs are converted into discrete values, which are assigned to various user defined states.

Using the above steps, the fuzzy logic system that is proposed in Fig. 2 is a multi-input and single-output (MISO) system, which is built using linguistic variables. It is composed of two input membership functions (speed and traffic density) and six rules/states.

A. Input Membership Functions (fuzzification)

Journey impedance, such as traffic congestion, is a significant contributor to stress during driving [24], [25]. As such, two input membership functions (MF) have been defined using the measures of speed (mph) and traffic density (car count), as these factors significantly contribute to journey impedance. These MF's were designed based on expertise knowledge and by observing patterns in the data.

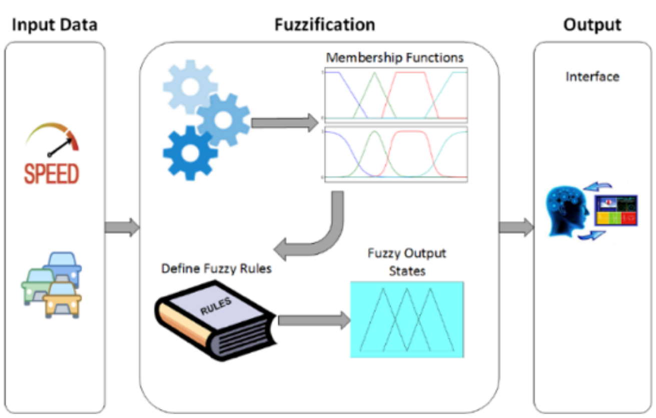


Fig. 1 High level design of the system

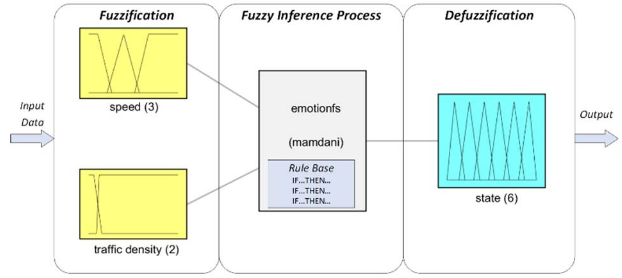


Fig. 2 Design of the fuzzy system

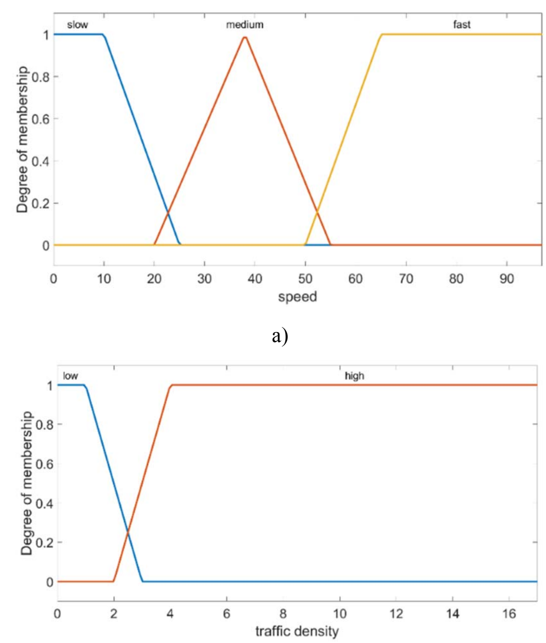
During the fuzzification process, the crisp input data (speed/traffic density) must be converted into linguistic variables [11]. In this instance, speed is a fluctuating variable that has been described using the following linguistic terms:

Speed (s) = {*slow, medium, fast*}

Fig. 3 a) illustrates the speed MF, which uses simple triangle functions to define each fuzzy set. The *slow* and *fast* fuzzy sets use a Trapezoidal membership function, whilst the *medium* set uses a Triangular function, which defines the parameters of the fuzzy sets. The input data is then categorized by its degree of membership, which illustrates the extent to which the data belongs in each category. For instance, if a vehicle was travelling at 10 mph its membership value would be set to 1.0 within the *slow* set. As the vehicle accelerates, its degree of membership within the *slow* category reduces and overlaps as it moves into the *medium* range.

Fig. 3 b) illustrates the traffic density MF, which is used to describe the number of moving cars in the lane(s) immediately ahead of the vehicle. This MF uses two Trapezoidal membership functions and has been described using the following linguistic terms:

Traffic Density (td) = {*low, high*}



b)

Fig. 3 a) Speed and b) Traffic Density input Membership Functions (MF)

B. *Fuzzy Inference Process (rules) and Defuzzificaiton*

The final stages of the process involved defining the rules and associated output states, which have been determined using expertise knowledge. Rules are the core of the fuzzy inference process and are represented by a sequence of IF-THEN statements [11]. Fig. 4 illustrates the six rules that have been defined for the system. The rules have been evaluated equally and relate to an output state (see Fig. 5), which has been defined using the following linguistic terms:

State (s) = {*Idling, Journey Impedance, High Urban Workload, Low Urban Workload, High Non-Urban Workload, Low Non-Urban Workload*}

For instance, if the driver is moving slowly and there is a high number of cars around then they are thought to be in a state of *Journey Impedance*, as the increase in traffic density is contributing to their slow speed. Equally, if the car is moving fast and there are a low number of cars around then they are experiencing *Low Non-Urban Workload*, such as driving on a highway. During the defuzzification stage, a centroid calculation has been used to combine the results of the rules and output a single value, which corresponds to the degree of membership of each of the output states in Fig. 5. The parameters of each output state have been defined in Table I.

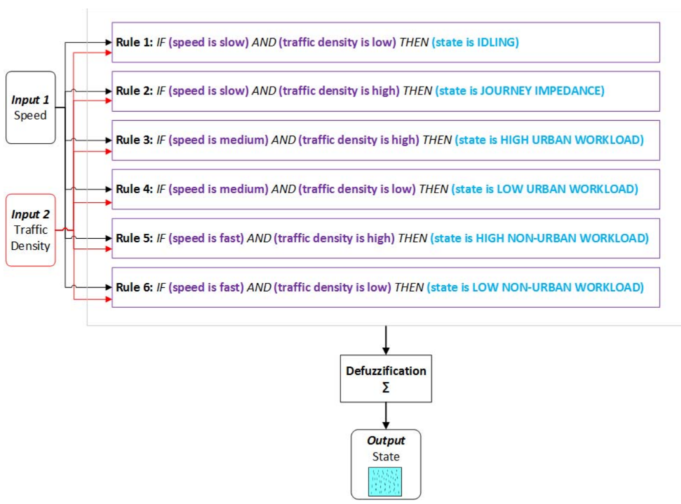


Fig. 4 Rules of the fuzzy system

TABLE I PARAMETERS OF EACH STATE OF THE FUZZY SYSTEM

State	Parameters
Idling	[0 0.5 1.2]
Journey Impedance	[0.8 1.5 2.2]
High Urban Workload	[1.8 2.5 3.2]
Low Urban Workload	[2.8 3.5 4.2]
High Non-Urban Workload	[3.8 4.5 5.2]
Low Non-Urban Workload	[4.8 5.5 6]

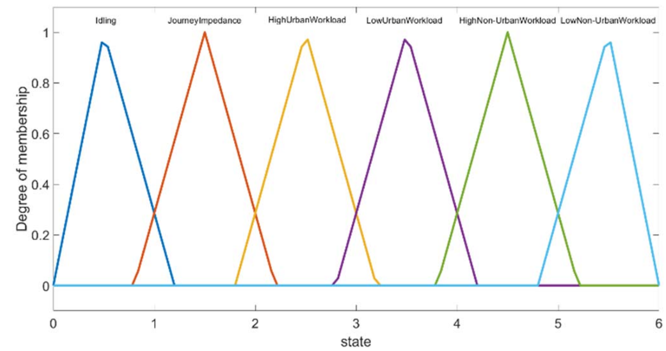


Fig. 5 Output states of the fuzzy system

C. *Data Analysis and Visualization*

Real world data collected during the study has been utilized to validate the system. Fig. 6 illustrates the generated surface plot that depicts the functional relationship between the dependent variable (output state) and the two independent input variables (speed and traffic density). The color bar in Fig. 6 corresponds to the output states in Fig. 5. For instance, occurrences of *Journey Impedance* are indicated by instances marked in the region of 1.5 on the scale (purple). This corresponds to the rules in Fig. 4, whereby speed is slow (in the region of 0 – 20 mph in Fig. 6) and traffic density is high (> 5 in Fig. 6).

The main purpose of the fuzzy system is to establish the context within which increased levels of driver stress occurs. The inflammation experienced by participants during each journey was inferred from cardiovascular activity. Using a previously established method [12], the psychophysiological dataset was labelled by splitting the data range into percentiles. Using the high frequency (HF) measure of heart rate variability (HRV), "stressful" labels were assigned to those data that fell into the bottom 33% of the HF distribution, i.e. HF HRV is inversely associated with markers of inflammation in the blood [26]. Fig. 7 illustrates the frequency of cardiovascular data points associated with increased inflammation across all six categories of driving context as defined by the fuzzy system. As it can be seen in Fig. 7, high inflammation was associated most frequently with those states categorized as *Idling* and *Journey Impedance*. This trend demonstrated an association between categories linked to low speed and increased levels of inflammation.

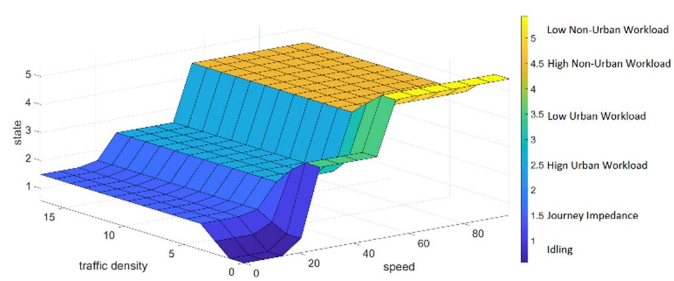


Fig. 6 Surface view of the output of the fuzzy system

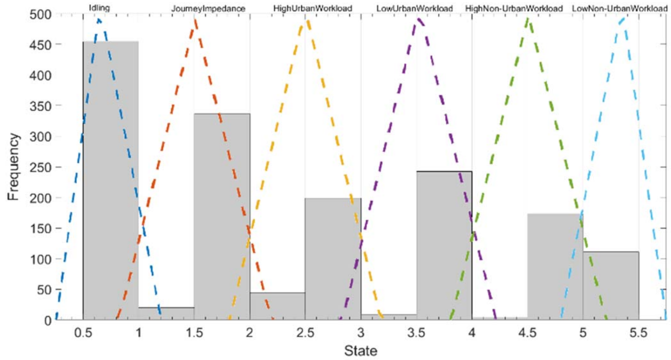
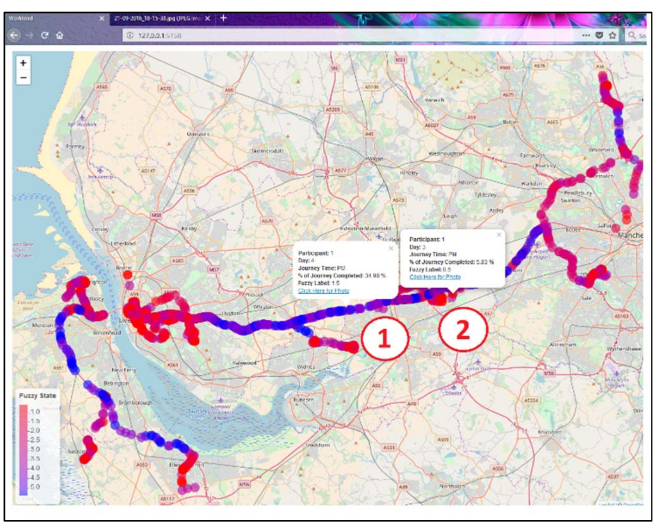
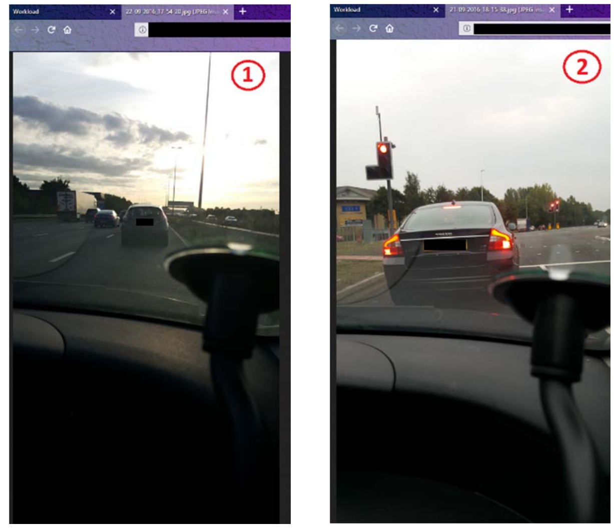


Fig. 7 Histogram of the output of the fuzzy system that have been labelled as stressful

An interactive application has also been created to establish the context of the fuzzy system. Fig. 8 a) illustrates an interactive map of all participants data that has been labelled as "stressful". The map illustrates the route that the drivers took throughout the duration of the study. As the purpose of the study was to collect data during daily driver commutes, the route rarely changed throughout the study for each participant. As it can be seen in Fig. 8 a), the route has been color-coded based on the fuzzy states. When a point on the map is clicked on, a bubble appears that depicts the participant's ID, the day that the data was collected, whether it was a morning or evening commute (AM/PM), the percentage of the journey that has been completed, the fuzzy label value that has been assigned and the associated photo. For example, instance one on the map has been assigned a fuzzy label of 1.5 by the system, which corresponds to *Journey Impedance*, whilst instance two has been allocated a fuzzy label of 0.6, which depicts a state of *Idling*. The associated photos in Fig. 8 b) verifies these states, as during the first instance the driver was in traffic, whilst the second photograph illustrates that the driver was stopped at traffic lights.



a)



b)

Fig. 8 a) Interactive application of the fuzzy system that illustrates all participant's aggregated data that has been labelled as stressful and b) photographs of the associated instances highlighted in a)

This application has been developed to establish the context surrounding the fuzzy system and to help users reflect on their data. By combining multiple streams of data together illustrates how complex data can be transformed into a simple and informative application.

V. Conclusions and Future Work

The purpose of the paper has been to detect different instances of driving context, via a fuzzy logic system, and to infer the association between inflammation and the context of real-life driving. This has been achieved by collecting real-world data, using a variety of sensors attached to the driver and vehicle, during the daily commuter journeys of eight participants.

The application of fuzzy logic allows the system to apply approximate reasoning to data in order to assign output states with a degree of membership that are based on natural language [27]. This is important for real-world applications whereby there is not a clear separation between objects and objects can be in more than one fuzzy set. Additionally, combining medically meaningful data with the fuzzy system allows the context of high inflammation (i.e. low HF HRV), which is associated with pro-inflammatory cytokines in the body, including interleukin 6 (IL-6), to be identified. By identifying the relative frequency of high inflammation within a specific category of driving we can assess the context of this behaviour via the interactive visualization, which allows multiple streams of complex data to be amalgamated into a simple interface. This outlet illustrates a variety of information, including the route of each driver, the fuzzy label and context (via the photographs) of stressful events. This interface provides an intuitive platform whereby participants can reflect upon their data. For example, by identifying instances of journey impedance and quantifying how many of those instances were associated with high inflammation we can assess where on the route this physiological response occurs and the context of those times. Extrapolating this on a national scale, potential stressful locations could be identified on a city-wide level to pinpoint areas of interest for city planners to investigate. This has the potential to not only reduce individual stress, via the interactive interface, but also the stress of the general population.

Future work aims to build on these findings by implementing a real-time fuzzy feedback system to detect stress and driving conditions as the driver is driving. This will allow us to measure the real-time impact of instant feedback on reducing stress, particularly during periods of journey impedance. Additionally, the fuzzy system could also be extended to incorporate other environmental markers, such as the presence of traffic lights. This would enable rule 1 to be refined to establish if the driver was sitting at the front of a traffic stream at a red traffic light or if they were parked.

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