The Affect-Aware City

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***Abstract*—The goal of smart cities can be summarized as optimizing the city's services (transportation, utilities, safety and many others) in order to improve the quality of life of its residents. A means to this goal is the heavy use of information and communications technology to give the city awareness of the real world and enable intelligent decision making. At the same time, the field of Affective Computing aims to give machines the ability to interpret and utilize human emotions. It is argued that emotions are an inseparable aspect of human intelligence. We thus propose our vision of the affect-aware city. By being capable of understanding the affective states of its citizens, the city's decision making processes can be brought in line with what truly matters to the people. We give an overview of the relevant affective states. We show how they can be detected individually and then aggregated into a global model of affect. The paper concludes with some inspiring applications that are possible in an affective city.**

***Index Terms*—Smart City; Affective Computing; Emotion Detection**

I. Introduction

The term *smart city* has been used for well over a decade. As a result, many definitions of the concept exist, each highlighting a different aspect [8]. The center of attention of all smart city initiatives are the challenges brought forth by the rapid growth of the population in cities. Examples of these challenges are environmental protection, and the provision of transportation, utilities, safety and education, just to name a few. Tackling these is essential for creating a more sustainable and livable city [23].

The definition of a smart city that best matches our understanding is the one given by Harrison et al. [27] with a strong focus on ICT. A multitude of deployed sensors deliver near real-time real-world data. The sensors may either be physical, such as cameras, meters for water, gas or electricity, RFID tags, environment sensors, implanted medical devices, induction loops in roads or telematics systems in vehicles, or they may come in the form of information that is automatically extracted from the web, social networks or smartphones. All sensors are interconnected into a large computing platform, where data is aggregated in a hierarchy of gateways, creating a big picture of the live state of the city. The information is made available to various city services which can then adapt to the behavior of the inhabitants. The inclusion of data analysis, modeling and prediction allows a shift of the decision making from human operators towards automated processes.

The advantages of a smart city with a focus on ICT become apparent in a number of applications. "Mobility on Demand" for instance provides lightweight electric or human-powered vehicles for rent by sensing the current need for mobility, managing the supply of vehicles and monitoring the current traffic [39]. In a similar vein, RFID technology can be used to identify vehicles in the context of parking lot management to automate payment and guide drivers to empty parking spaces [45]. Monitoring and predicting the demand and production of energy, combined with dynamic pricing, can be used for smoothing peaks in the energy consumption. Similar results have been reported for water supply [27].

Smart cities have been likened to living organisms. Information is collected through sensory receptors. The communication infrastructure becomes the nervous systems and the computing platform is the brain. Similarly to an organism, the city then monitors its service sub-systems and reacts to changes in order to maintain homeostasis [60]. This raises the notion of considering affect in a smart city as well. It has been shown that emotions as one aspect of affect play an important role in rational decision making [41]. The amount of information to process in order to reasonably consider every possible alternative when making a decision is far too large. Also, pure logic-based reasoning has shortcomings when handling the uncertainty immanent in real-world problems. Emotions serve to rapidly pre-filter certain alternatives, so that the costly reasoning process can be focused on the more desirable ones [10]. Emotions are an integral part of human thinking. For a city to be truly "smart", it thus also needs to take affect into account.

In addition to emotion playing an important role in decision making, emotion has been shown to be a central component of human behavior [17]. In order to adapt the city's services and to form predictive models, it is not sufficient to sense *what* people are doing, but also to understand *why* they are behaving in a certain way. Considering affective states is thus essential for achieving real-time awareness of the city's inhabitants. Emotions also influence judgment and perceived life satisfaction [32]. City planners can make use of the gathered affective data to detect positive or negative trends developing in the city and to take early countermeasures. Answering subjective questions like "Which part of the city is the best?" requires the consideration of affect.

In this paper, we propose our vision of an affect-aware city that is able to understand, interpret and adapt to the affective states of its citizens. We aim to change smart cities in a way that is similar to how affective computing has

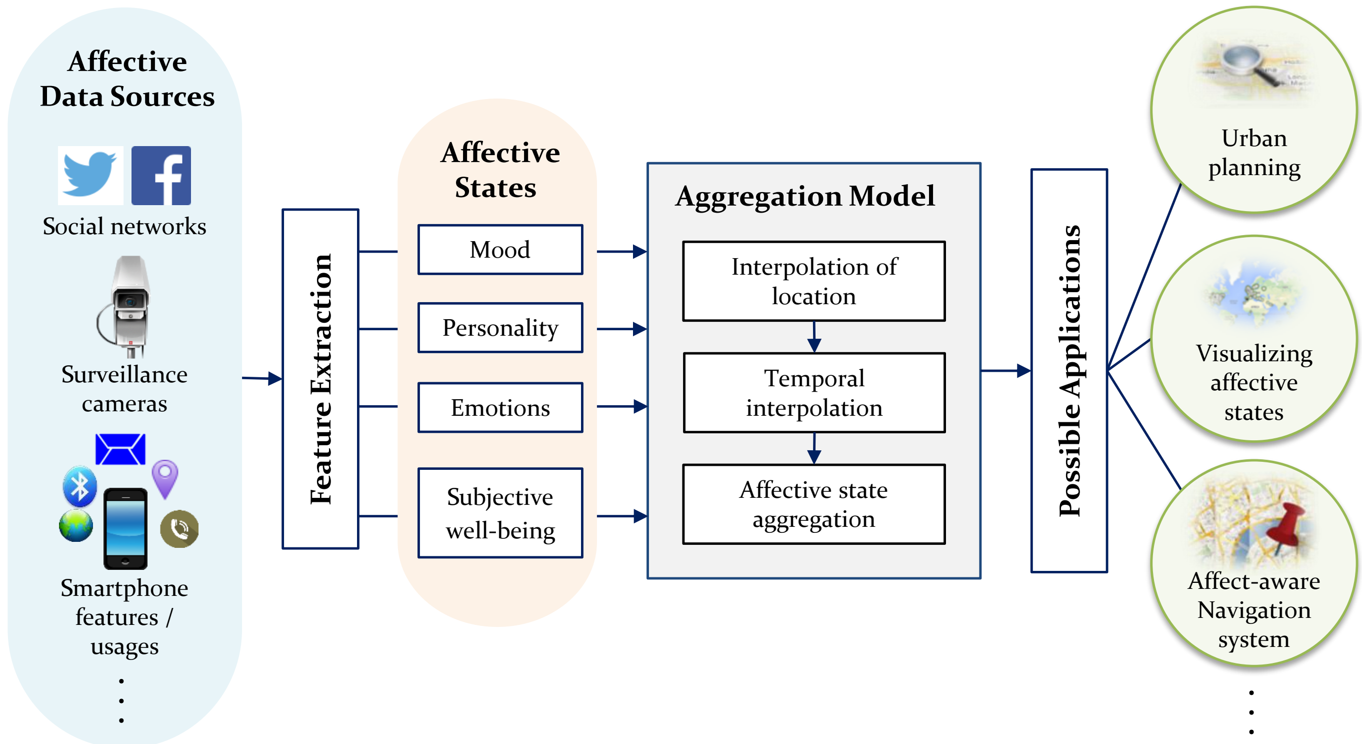

Fig. 1. Conceptual framework of the affect-aware city that is proposed in this paper. The affective states of the citizens are sensed from a variety of sources by extracting features and applying machine learning techniques. The affective data is then aggregated over time and space and integrated into a model of affect in the smart city that can be used in a number of applications.

changed human-computer interaction [49]. Figure 1 shows the conceptual framework of our affect-aware smart city. The paper begins by defining the relevant affective states and their interrelationships in Section II. Two major research challenges in the new field of affect-aware cities are the *detection* and *aggregation* of affective data in an urban scenario. It is to be expected that techniques to detect emotions that were developed in a lab setting are not directly applicable to a smart city context. In Section III, we discuss how the sensors and the communication infrastructure that are available in a smart city can be utilized to detect affect. The measurement of emotion is a highly individual process. Key aspects like appraisal and physiological response are very specific to a person [59]. Aggregating the heterogeneous affective data from different people in different places at different times into one consistent spatio-temporal model is thus another major challenge which we address in Section IV of this paper. In Section V, we describe a few example applications that will be made possible in an affect-aware city, in the hope that they will inspire research in this field. Section VI concludes the paper.

II. Affective States

There are a number of different, but related phenomena that influence people's behavior. The ones that are most relevant in an affect-aware city are: emotion, mood, personality and subjective well-being. Throughout this paper, we will refer to them simply as *affective states* for lack of a more fitting hypernym. This section gives an introduction to these states and their interrelationships and reviews models for their representation. Figure 2 gives an overview of the concepts discussed here.

Emotion is a phenomenon that occurs when a human is exposed to a stimulus that triggers changes in the person's facial expression, gestures, voice, and physiology. A necessary requirement for an emotional episode to occur is appraisal, that is, the eliciting stimulus must be perceived as relevant to a person. The term *feeling* denotes the *subjective* experience of an emotion [56]. In the literature, emotions are represented in either the discrete or the dimensional model, and there is an ongoing controversy about the neurobiological justification of these models [26]. The discrete model represents emotions by words and categorizes them into groups based on their features. The most commonly used group is called *basic emotions*. It consists of emotions that can be found in many cultures: anger, disgust, fear, happiness, sadness, surprise [18], anticipation, trust, and joy. These basic emotions can be combined into more complex ones. For example, the two basic emotions of joy and trust can be combined into the complex emotion of love [51]. In the dimensional model, each emotion is expressed by a number for each dimension. This makes it a useful data format for representing emotions. An emotion is mapped to a point in a multidimensional space, where the number of dimensions varies depending on the model used. The circumplex model by Russell has the two

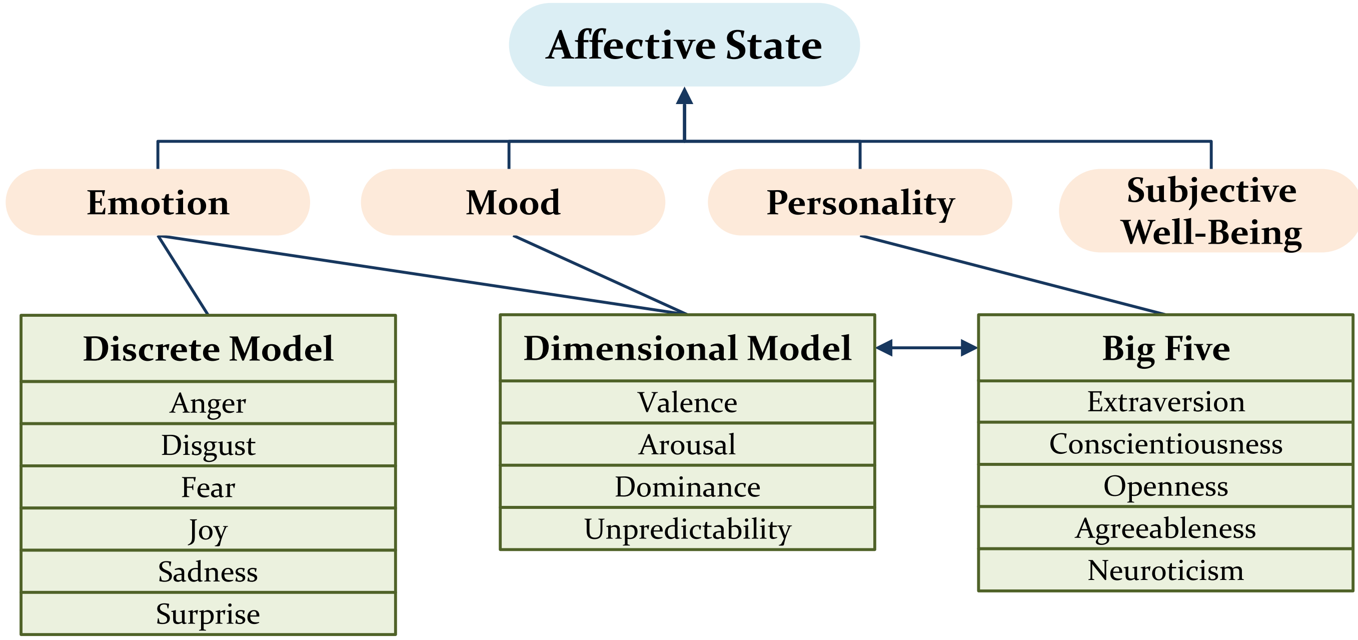

Fig. 2. Overview of the types of affect considered in our scenario and their computational representation. Emotion can be represented in the discrete and the dimensional model. The latter has the benefit that it can also be used to describe mood, and there exists a mapping to the Big Five model of personality.

dimensions *valence* and *arousal*. Valence is associated with the degree of pleasantness or unpleasantness of an emotion and corresponds well with the common intuition of good and bad emotions. It is also termed *pleasure* in some models. Arousal refers to the level of physiological change in the person, i.e., whether an emotion makes a person feel calm or excited [55]. A third dimension, *dominance*, has been added by Mehrabian. It expresses whether an emotion makes one feel in control of one's surrounding (e.g., anger, relaxation) or feeling controlled (bored, anxious, etc.) [38]. It has been proposed to use *unpredictability* as a fourth dimension to distinguish appraisals of novelty from appraisals of expectedness. However, its descriptiveness is lower than that of the other dimensions [20]. There also are recent works dedicated specifically to the representation of emotion in a computer. For example, many of the considerations regarding an emotion markup language proposed in [58] also apply to our affect-aware city scenario – even though our requirements differ as will be outlined in Section IV.

Mood is an affective state that is very similar to emotion. Compared to emotion, mood has lower intensity, less impact on a person's behavior, but longer duration. While emotions are focused on a particular stimulus, moods are typically less specific to a reason [56]. Because of its similarity to emotion, the same dimensional models can be used to represent moods. This is convenient when working with them in an affective computing context [22].

Personality can be defined as a pattern of affect, behavior, cognition, and goals that is consistent over long timespans. It describes a person's predisposition to experience certain emotions [53]. On the broadest level of abstraction, personality traits are described by five dimensions, the so-called "Big Five". Each of these dimensions is associated with a list of features: Extraversion (activity and confidence), Agreeableness (social adaptability and likability), Conscientiousness (competence and self-discipline), Neuroticism (emotionality, or the opposite of emotional stability), and Openness (intellectual interests) [29]. There exist various tests to measure these five personality traits. However, it must be noted that reducing a complex phenomenon such as personality to such a small number of traits is not without controversy [48]. Despite this criticism, it is a useful model to represent personality computationally. Its most useful feature for our scenario is the existence of a mapping between the PAD dimensions of emotion (pleasure, arousal, dominance) and the Big Five personality factors [37].

Subjective well-being refers to a person's judgment and evaluation of his/her life. The evaluation consists of emotional reactions, moods, and cognitive judgment of satisfaction. More colloquially, it is referred to as "happiness" [15]. It is a relevant type of affect here, because it constitutes an important optimization criterion for improving a city. Extraversion and neuroticism have been found to be highly correlated with positive and negative affect, respectively. This makes personality a good predictor of subjective well-being [15].

III. Sources of Affective Data

Urban planners in a smart city rely on the data obtained from deployed physical sensors to monitor the quality of the environmental parameters. However, this does not directly reflect how humans actually perceive their environment and the city's services. In this section, we illustrate how people's affective states can be obtained from different data sources that are available in a smart city. The focus lies on a detection in natural ways without requiring specialized equipment or particular participation.

One of the most easily accessible public data source that can be used in affect detection are social networks and blogs such as Facebook and Twitter. People use them to share their opinions and express their feelings [47]. It has been shown that users of social media are likely to post authentic and reliable information about themselves [36]. This makes such platforms very suitable for affect detection in an affect-aware city.

Approaches based on text analysis are suited for extracting moods and emotions from social networks. For instance, a linguistic characteristics analysis on the written posts made by individuals on their blogs can be used to infer negative and positive moods [33]. Applying this technique to Twitter update messages allows to reveal information about public moods and emotions [3]. Additionally, the Twitter "hashtags" can be harnessed to extract individual mood states categorized by valence and arousal [7] as well as emotional states categorized by basic emotion labels [40].

The Big Five personality traits can be effectively predicted by performing a feature-based analysis of the public data available in Twitter and Facebook profiles. In the case of Twitter, personality traits can be predicted based on the three publicly available counters "following", "followers" and "listed" [52]. Besides these three counters, the authors of [24] use additional information that people reveal in their twitter profiles, such as the number of mentions, replies, hashtags, links and words per tweet. Specific to Facebook, profile data including personal information, activities and preferences [24] as well as user interaction parameters such as the number of friends and wall posts [44] can be used to predict individual personality traits.

Mobile devices such as smartphones are ubiquitous, unobtrusive and have become an essential part in people's daily lives. They are thus another valuable tool for collecting affective data in the context of an affect-aware city [42]. Touch behaviors have been investigated as a way to recognize emotional states. They have been used successfully to determine the user's emotion dimensions valence and arousal [21], and to classify the user's emotional state into Ekman's six basic emotions plus a neutral label [30]. Furthermore, the human voice recorded by a mobile phone can reveal affective states such as emotion, mood, stress, and mental health [57].

Smartphone usage patterns also provide insight into many affective states. For example, there is a significant correlation between the Big Five personality traits and features derived from call logs, SMS, Bluetooth and application usage [12][6]. Usage patterns of SMS, email, phone calls, applications, web browsing and location can also be exploited to reveal and predict the valence and arousal dimensions of the user's mood [34]. It has been shown that subjective well-being can be inferred similarly [2].

Surveillance systems have become an integral part of the urban infrastructure. They are deployed for purposes of human identification and crowd behavior monitoring. In our affect-aware city scenario, they can be used to non-intrusively collect affective data from facial expressions, sounds, dynamic body motion and gestures [62][5]. For example, human faces provide rich sources of affective information [61]. Also, gestures and body language have been used as means to infer affective states [11] [14]. Multi-modal approaches that combine facial expressions and gestures obtained from surveillance cameras achieve even better detection accuracies than single modalities alone [46].

IV. Modeling Affect in a City

The sources described above allow the detection of the relevant types of affect. In order to make use of this gathered information, it needs to be aggregated into a uniform spatio-temporal model of affect in the city. The goal is to be able to make statements about quantities of affect that are present in certain regions of the city. This is an open research challenge. In this section will give an insight to the problems and propose directions for their solution. The two key areas – interpolating missing data of *individual* affect, and *aggregating* individual affect into an affective state of a region – are discussed in their respective sections.

A. Individual Affect

Most of the data sources described above measure affect for *one person* at one point in time or during a time interval. This data may be incomplete mainly for two reasons. The data may or may not include location information which is necessary to map affect to regions of the city. Also, the data samples may be sparse in time (e.g., infrequent posts to social networks). We propose solutions to each of these identified problems separately.

Mapping the detected affective state of a person to a region of the city requires information about the person's location. Depending on the source of the affective data, this information may not always be available. We therefore need mechanisms to fill in the missing location data. Interpolation and prediction of an individual's position is facilitated by a high regularity of movement patterns. For example, people spend the majority of their time in very few different locations (40% of the time in their top two locations). The choice of location additionally shows a high periodicity in multiples of 24 hours. Furthermore, the basic statistical properties of individual mobility patterns are nearly identical after scaling. Putting this together allows calculating the likelihood that a person is in any location at any given time [25].

The regularities of movement patterns and partial knowledge of the movement history is exploited in mobility management of mobile phone networks. In this context, the next location of a user must be predicted in order to pre-allocate resources at the next access point that a user will connect to for enabling a seamless handover [35]. The mobility patterns developed for mobile phone networks can also be used to predict a person's location in the affect-aware city scenario.

Since many of the proposed sources of affective data rely on a person's interaction with social networks or their smartphone, the frequency of affect updates may be low. To get a more complete view of a person's affective state, the missing data needs to be interpolated. The possibility and necessity of interpolation strongly depends on the type of affect considered. For example, dispositional affect is stable over a two month period [64], and personality traits measured over intervals of 3 to 30 years have been shown to be highly correlated [9]. It is clear that no temporal interpolation is needed in this case.

Typical durations of emotional episodes are much shorter. 80% of the emotional episodes in a study were shorter than 30 minutes. Intermediate thoughts with a valence opposite to the emotion shorten its duration, while thoughts about the stimulus that have the same valence lead to a prolongation of the episode. Also, social sharing of the events increases the duration of the emotion [63]. These findings give a good indication for how long a detected emotion is valid before a person reverts back to a neutral emotional state. If emotions are detected from a social network, subsequent posts can be assumed to refresh or cancel the emotional state, depending on the valence of the message.

Mood change over time has been studied in the context of embodied conversational agents where the goal is to simulate mood change as plausibly as possible. If mood is represented as a point in the same dimensional space as emotion (e.g., pleasure, arousal, dominance), then an emotion can be thought of exerting a force that pushes or pulls the mood in a certain direction. In the absence of emotions, mood slowly converges towards a default mood point which can be derived from personality traits [22]. The pleasure dimension of mood can also be interpolated by using mood prediction. A history of a person's mood valence together with additional context information can be used to learn a prediction function that indicates the most likely mood state the person is in at a future time [65].

B. Aggregated Affect

So far, we discussed the affective state of a single person. However, in an affect-aware city, we need to assign affective states to entire regions in order to make a dynamic map of affect. It is thus necessary to aggregate the individual affective data. Let us consider two simple examples to illustrate the challenges of aggregation: After a sports event, two busses full of happy and sad fans of the winning and the losing team respectively drive past each other. They are now in same region. However, the emotions of the fans obviously do not average. The result is not two busses full of emotionally neutral people, so assigning this label would not be accurate. This is not to say that emotions do not influence each other. As a second example, consider a fearful person who meets a group of confident friends. The fear that this person experiences will likely be reduced due to the reassuring effect of the group. The circumstances under which individual affective states influence each other need to be studied carefully in order to allow an accurate aggregation.

Psychology gives an insight to the qualitative mutual influence of the affective states of members of a group. This concept is called *contagion*. Generally it can be said that contagion is strongly tied to attention, i.e., the more attention is given to a person, the more the own affective state will change. The inverse direction also holds: if no attention is given to a person, no emotional contagion occurs [28]. Under the assumption that most people in a region dedicate little attention to others, it can be concluded that the affective state of a region must be represented as a mixture, rather than a single clean state as for an individual. The amount of contagion is proportional to attention, which in turn may be estimated from the connectedness of people in a social network. Connectedness may thus give a first approximation to how much individual emotions even out in a group.

There has been evidence that moods of negative valence have a bigger impact on the mood of a group than those with positive valence. Further, it has been hypothesized that emotion that is expressed with higher energy leads to more contagion [1]. In addition, the personality trait extroversion is positively correlated with improved transmission of emotions [4]. At this point, we assume that valence, arousal and extroversion can be measured for an individual. This data together with the findings above can then be used to quantitatively model emotional contagion. Application of the emotional contagion scale [16] can further improve the accuracy. It is a 15 item scale that measures susceptibility to the emotions of others. This model can predict how much a person feels an emotion of someone else. It has been found to be positively related to the personality trait of neuroticism. The measured neuroticism of a person may thus be used as a metric to define how much individual emotions mix.

C. Taking it One Step Further

As described earlier in this paper, a smart city may be equipped with a large number of sensors that are unsuitable for detecting affect directly. Conditions that may be measured include weather, light, noise level, traffic density, crowdedness or the amount of crime in an area. It is highly likely, however, that these quantities have an influence on people's affective states [13]. An open research objective is to find correlations between the measurable variables of a region and its aggregated affective state as detected from its inhabitants. A machine learning system could be trained on this data which would allow to predict the affective state directly from the sensed quantities. This approach is very similar to the detection of emotion in humans. Emotions cannot be measured directly. Instead, they are predicted from the physiological signals of a person (heart rate, skin conductance, etc.) [50]. The variables of the city constitute the city's "physiological signals" from which emotions could be predicted directly. This would conclude the transition from detecting individual affect to predicting the affect of the city as a whole. Such a prediction of how affect is formed could be used as a tool in optimizing the city's services and improving the decision making process.

V. Applications

After discussing a computational representation of affect in a city in the section above, we propose potential applications that become possible in an affect-aware city. We hope that they will inspire research in this field.

Urban planning is the process of regulating land use to optimize aspects like resource consumption, transportation, and safety in the face of rapid urban growth. Negative trends in the city must be recognized as early as possible, and a large variety of sensors are available for this detection process [66][31]. If problems are identified quickly, early countermeasures can be taken. An awareness of the affective state in the city facilitates this detection of problems. The prevalent affect in an area serves as implicit feedback on its livability. A predominance of negative affect may be an indicator for undesirable conditions. Also, there are problems that are obvious to inhabitants, but are hard to measure with statistics and facts. Consider the following examples: Even without available crime records, people have a good intuition of the safety of a neighborhood. Similarly, the amount of visual degradation and littering is hard to measure, but can be judged subjectively without effort. The same density of traffic may not always be perceived as disturbing, depending on external conditions like expectedness, current stress level, time of the day or weather. In all these examples, affective states can be harnessed to understand how citizens truly perceive their environment. This subjective feeling may differ greatly from measurable statistics.

Affect-awareness also enables new forms of communication. Traditionally, the choice of partners for online group communication is either based on pre-existing relationships (e.g., friends, workplace, sports team) or based on similar interests or location (forums, chat groups, hashtags) [19]. The desire for indirect, semi-anonymous group communication is indicated by online services like Twitter where individuals can send messages to groups of likely interested users. In an affect-aware city, communication groups can be formed spontaneously, based not only on topic, but also on location and matching affective state. In many situations, there may be a desire to send messages to groups with a specific mindset: In order to start an interesting discussion about controversial projects or places in the city, communication partners with a strong and possibly opposite opinion may be preferred, whereas very personal and sensitive issues are best shared with those who feel the same. During an event that takes place close to a residential area, people may want to share their thoughts mostly with others with the same attitude towards it (e.g., participants enjoying the event, or upset residents). Furthermore, target groups can be based on emotions (e.g., relaxed, happy, sad) or based on their current desire to communicate. Using affective data for finding communication partners nearby is more specific than the traditional topic-based approach, because it also takes the participant's feelings towards the topic into account.

When using a navigation system, the fastest way to get from A to B is not always the only criterion to optimize for. Other factors like the purpose of the trip, preferred locations or external conditions like weather and traffic may also play a role in choosing a suitable route [43]. This is especially true for pedestrians and bicyclists who are often willing to sacrifice time to seek an alternative route that provides more safety, comfort or room to explore [54]. This can be accomplished by designing a navigation system that also considers the affective state of both the person navigating and the area being navigated. There is a multitude of reasons why a pedestrian or bicyclist may choose to avoid areas with negative affect: Emotions like *fear* and *anger* indicate danger and should be avoided by travelers feeling *afraid*. *Stress* may be felt in areas of high traffic or crowdedness which are undesirable for bicyclists. The emotion *disgust* indicates places that are unsuitable for relaxation. Likewise, there are reasons to seek areas with positive affect: A detour through a relaxing area can be acceptable when someone is feeling stressed. The emotion *relaxed* may also be correlated with higher safety to ride a bicycle in an area. Furthermore, someone may want to seek locations with increased *surprise* when they are *curious* and in the mood to explore. Reasons to seek or avoid areas with a certain affective state are as manifold and personal as affect itself [59].

VI. Conclusions

We proposed our vision of a smart city that is capable of interpreting and harnessing the affective states of its citizens. The detection of affect by a computer has received a tremendous amount of attention. As a result, many techniques exist, some of which can be used to sense affect unobtrusively in an urban scenario. We gave a few examples of applications that would benefit from the availability of affective data. A look at the literature on affective computing quickly reveals countless more applications that could be extended to a smart city context. To realize our vision, new methods of sensing affect in a smart city need to be found. This includes the repurposing of existing sensors in a creative way to derive affective states. It is also necessary to investigate more deeply how large quantities of a affective data, sensed from many individuals, can be made manageable in a computational framework. We believe that affect-aware cities are a field of research that deserves attention in the near future. It has applications in smart city initiatives and could be used as a tool in emotion research.

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