Decision Support for Route Planning to Reduce Heat Stress Considering the Time of the Day

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Heat stress is a serious risk, which affects in particular groups like elderly or patients with multiple sclerosis or heart disease and is especially pronounced in cities. Developments like the ageing of society, the increasing urbanisation (urban heat island effect) and the climate change are increasing the risk that people are affected by heat stress. One way to reduce those risks is to adapt the everyday behaviour. To encourage and support such a change of behaviour, we propose a two step approach. The first step is a route planer for pedestrians that can find a route with minimal heat exposure. The second step is a tool that supports the user to select the point in time with a minimal risk of heat stress, considering e.g. the opening hours of a shop. The route planer is then used to calculate the heat stress and present the optimal route at that point in time. We evaluate our approach for the city of Karlsruhe. Our results show that the combined approach, as well as only its single steps, can reduce the heat exposure and therefore the heat stress for typical daily tasks.

1 Introduction

Heat is an important factor to human health and comfort. High temperatures cannot only lead to a discomfort,such as sweating, it also has serious negative effects on the health as well as on the ability to work.

In numerous studies an increase in both mortality and morbidity has been associated with a high ambient temperature (Basu 2009). The most well known example in recent history is the 2003 heat wave in Europe. In France alone 19490 heat related deaths were to be mourned, an excess mortality of 60% for the whole country. In Paris the excess mortality reached 142% (Robine et al. 2008).

Certain groups are especially vulnerable to heat stress such as older people or people with health problems (Ebi et al. 2004; Hübler, Klepper, and Peterson 2007). For patients with multiple sclerosis an increased body temperature can lead to a worsening of their symptoms (Davis et al. 2010).

Developments like the ageing of society, the increasing urbanisation and the climate change is making the adaptation to heat stress danger more and more important. Due to the tendency that a rising number of people is moving into the cities (Economic and Social Affairs 2014), the urban heat island effect (UHI) is gaining more importance in the future. The UHI effect states that an urban area can be 8 °C to 12 °C warmer than the rural areas (Prashad 2014). This increased temperature can be caused by several facts. One example is that urban materials such as asphalt, concrete, and bricks are storing the energy from the sun and releasing it later to their surrounding (Prashad 2014).

There are several possiblities that can been taken to reduce the heat stress. These range from urban planning measures to the implementation of heat warning systems (Ebi et al. 2004). But these steps are only available on large scale projects. Individuals can reduce their heat stress by adapting their everyday behaviour. In this work we present a two step approach to help individuals in doing so.

In a city, most typical activities are in walking distance. These can range from going to a grocery store to the visit of a doctor. And while these activities can not be omitted, it is possible to use different routes or change the time when they are conducted. In doing so, one can easily reduce the heat stress without any negative impact on the quality of life.

In this paper we use this reasoning into a two step approach to help individuals reduce their heat stress. First, we apply a time dependent routing algorithm to compute the optimal path in regard to the heat stress. This algorithm is then used to determine the optimal point in time to conduct typical everyday activities.

1.1 Related Work

1.1.1 Heat Stress

The impact of heat on the human body has long been a subject of study. In particular , the term thermal comfort plays a key role, which describes climatic conditions consider comfortable, i.e. neither to warm nor to cold.

Heat can be defined in several ways, where the most simple one is the air temperature. But other, more in depth approaches consider additional factors such as e.g. humidity and physical activity (Staiger, Laschewski, and Grätz 2011; Hübler, Klepper, and Peterson 2007). Staiger et al.(Staiger, Bucher, and Jendritzky 1997) state that only a complete heat budget model of the human body is sufficient to make any reliable statements regarding the influence of heat on the body. They present such a model and update this model to include factors such as sweating in a follow up paper(Staiger, Laschewski, and Grätz 2011).

As such exhaustive models are quite difficult to compute and the necessary data is not always available, heat indices are often employed. The most well known indices that consider a complete human heat budget model are the following: (1) Steadman's heat index (Steadman 1979a1979b), (2) the predicted mean vote (PMV) (Fanger 1973), (3) the perceived temperature (Staiger, Bucher, and Jendritzky 1997; Jendritzky, Staiger, et al. 2000), (4) and the universal thermal climate Index UTCI (Jendritzky, Bröde, et al. 2010).

For all these indices the following meteorological parameters are important: (1) air temperature, (2) vapour pressure, (3) wind velocity (4) and mean radiant temperature of the surroundings (Matzarakis, Mayer, and Iziomon 1999).

Based on the availability of data, in this paper we will use Steadman's heat index (Steadman 1979a) and, as a simple comparison measure, the air temperature. To compute an approximation of the heat index we use the formula published by Stull (2011, p. 77).

1.1.2 Time Dependent Routing

Several research projects have considered environmental factors for pedestrian routing in the paste. The AffectRoute routing algorithm proposed by Huang et al. (2014) for instance takes the affective responses to the environment into account, e.g. to find a route that a person considers safer. Sharker, Karimi, and Zgibor (2012) are proposing a method to find a health optimal route, considering several environmental factors like complexity of the walking trail (slope etc.) and weather (only "Good", "Fair" or "Bad"). A method to find a route with a minimal pollution exposure has been proposed by Hasenfratz (2015) in his PhD thesis.

The NaviComf framework for pedestrian routing proposed by Dang, Iwai, Umeda, et al. (2012, 2013), enables to improve the comfort considering environmental factors varying over time. The proposed framework uses a multi-factor cost model for the evaluation of the route and enables them to consider heterogeneous environmental information from multi-modal sensors like air temperature and humidity. To find a optimal route Dang, Iwai, Tobe, et al. (2013) are proposing three different algorithms, a bounded depth-first search algorithm, an adjustable dynamic planning algorithm and a heuristic particle planning algorithm. As a sample application, the authors implemented a routing app for thermal comfort navigation. The meteorological used for this sample application have been collected using a network of 40 micro-climate sensor nodes which detected air temperature and relative humidity.

In contrast to the existing work, we contribute an approach which does not rely on extensive sensor networks. We achieve this by combining remote sensing data with in-situ weather stations and the use of a static routing algorithm.

2 Minimize Heat Exposure

We are presenting a two step approach to supported people to reduce their heat stress risk in their everyday life. First we are presenting an approach to find a route for pedestrian with a minimal heat exposure. On this basis, we show an approach to find a point in time with a minimal heat exposure, for instance to go shopping in a supermarket.

2.1 Finding a Route with Minimal Heat Exposure

2.1.1 Modelling as a Time-Dependent Routing Problem

Finding a route with minimal heat exposure can be modelled as time-dependent routing problem, where the edge weighting function is not static and instead may vary over time. Subsequently, many speed up techniques developed for static routing problems like bi-directional search cannot simply be applied (Delling et al. 2009).

Below, we are representing the road network as undirected graph $G = (V, E, w_d, w_h)$, where V is the set of vertices or nodes (e.g. junctions) and $E \subseteq V \times V$ is the set of edges (e.g. road segments) each connecting a pair of nodes. Furthermore $w_d : E \to \mathbb{R}_{\geq 0}$ and $w_h : E \times T \to \mathbb{R}_{\geq 0}$ are to edge weighting function, at which:

- $w_d(e)$ is the length of the edge e, and
- $w_h(e, t)$ is the heat exposure of edge e at time t.

Hereafter, a path p from node v_0 to node v_k starting a time t_0 is denoted as sequence of edge time pairs $((e_{v_0 v_1}, t_0), (e_{v_1 v_2}, t_1), \ldots, (e_{v_{k-1} v_k}, t_{k-1}))$, where t_i is the time at which node v_i is leaved. The weight of an edge is fixed at the time the traversing of the edge is started (the so-called frozen link model, Orda and Rom 1990). The time t_i can be computed as follows: $t_i := t_{i-1} + t_{walk}(e_{v_{i-1}, v_i})$ where $t_{walk}(e_{v_{i-1}, v_i})$ is the time needed by a pedestrian to traverse the edge e_{v_{i-1}, v_i}. The starting time t_0 is ether given or set to 0.

To compute the weight of a path $w_h(p)$ the following formula can be applied:

$$w_h(p) := \sum_{(e,t) \in p} w_h(e, t). \tag{1}$$

Those means we are looking for the path p^* from a node v to a node u that has the minimal weight of all possible path from v to u. Below, we are using $w_h(p, t)$ to denote the weight of the path p starting at time t.

The time-dependent routing problem is $\mathcal{NP}$-hard, if it is not allowed to wait on a node and the FIFO (first in, first out) property is not fulfilled (Orda and Rom 1990). An edge weighting function $w : E \times T \to \mathbb{R}_{\geq 0}$ stratifies the FIFO or non-passing property if for all

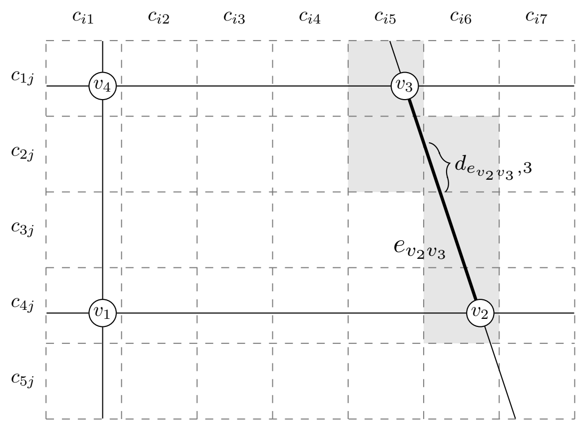


Figure 1: An example for the raster to edge mapping.

edges $e = (u, v) \in E$ and all points in time $t, t' \in T$ with $t \leq t'$ the following in-equation is met (Ahn and Shin 1991):

$$t + w(e, t) \leq w(e, t'). \tag{2}$$

In other words, a weighting function w fulfils the FIFO property if the numerator (change of the edge weight) decreases not faster than the denominator (change in actual time) increases, i.e. the slope of the weighting function is greater or equals to -1 (Kaufman and Smith 1993).

Usually, we cannot assume that w_h fulfils the FIFO property, because the function most of the time depends on the air temperature and the air temperature can decrease more than -1 over time. Since, most people are not willing to wait at a node as well, finding a route with a minimal heat exposure is $\mathcal{NP}$-hard. Therefore, hereafter the edge weighting is frozen at the starting time t_0 so that we have static route planning problem and classic algorithms like Dijkstra's algorithm (Dijkstra 1959) can be applied.

2.1.2 The Edge Weighting Function

To find a route with a minimal heat exposure it is key to define the edge weighting function in an appropriated way. At this, it is not sufficient to only take the actual thermal comfort value in to account, we also must consider the time a person is exposed to the heat. Below, we assume that the time of exposure is proportional to the length of the edge w_d (following Hasenfratz 2015). Based on this assumption we are defining the edge weighting function w_h as follows (cf. Hasenfratz 2015):

$$w_h(e, t) := \sum_{c \in Intersec(e)} d_c \cdot h_c(t). \tag{3}$$

Here, the thermal comfort values (like air temperature or heat index) are represented as time-dependent raster $H(t) = (h_{ij}(t))$, where $h_{ij}(t)$ denotes the thermal comfort value in raster cell c_{ij} at time $t \in T$. In the formula above, $Intersec(e)$ is the set of raster cells intersected by the edge e and d_c the length of the intersection of e with raster cell c. That is, to obtain the edge weight, the value of each intersected raster cell is weighted with the length of the intersection and then accumulated, as shown in figure 1.

Using the actual thermal comfort measures – air temperature and heat index – we get the following edge weighting functions:

$$w_{T_a}(e,t) = \sum_{c \in Intersec(e)} d_c \cdot T_a(t,c), \tag{4}$$

for the air temperature and respectively:

$$w_{HI}(e,t) = \sum_{c \in Intersec(e)} d_c \cdot T_{HI}\left(T_a(t,c), RH(t)\right) \tag{5}$$

for the heat index. Here, $T_a(t,c)$ is the air temperature in raster cell c at time $t \in T$, $RH(t)$ is the relative humidity at time t and T_{HI} is Steadman's heat index. How we obtained those values is described below in section 3.1.

2.2 Finding the Optimal Point in Time

Apart from selecting a route with minimal heat exposure the risk of heat stress in the everyday life (e.g. go shopping in a supermarket) can massively be reduced by selecting the appropriate time for this action. That's because usually, the heat exposure is highest at middays and significant lower in the morning or evening.

We are proposing an approach for a decision support tool that can help to find an optimal time for a certain type of location defined by a search criteria, that is within a specified radius. To obtain that goal, we are using three steps:

1. Perform a nearby search originating from a given starting point s (e.g. address or GPS coordinates) to find all locations L that fulfils a certain search criteria (e.g. is supermarket or pharmacy) within a specified radius r (e.g. 500 m).
2. For each location $\ell \in L$ found in step 1, determine the point in time t^* with the lowest heat exposure.
3. Create a ranking of the locations in L based on the minimum heat exposure found in step 2, so that the location with the lowest heat exposure has rank 1, that with second lowest rank 2 and so on.

The steps 1 and 3 are not very complicated, so we are focusing on step 2.

2.2.1 Modelling as a Optimization Problem

If we are search for the optimal point in time for a location ℓ we should consider certain constrains like the opening hours $[t_{open}(\ell), t_{close}(\ell)]$ of a location $\ell \in L$. As the objective function to minimize we are using the heat exposure of the optimal path between the starting point s and a location ℓ as proposed above. Those, finding the point in time with the minimal heat exposure means to minimize the following objective function $h(t, \ell)$:

$$h(\ell, t) = w_h(p^*, t) = \min_{p \in P_{s\ell}} w_h(p, t) = \min_{p \in P_{s\ell}} \sum_{(e,t') \in p} w_h(e, t'), \tag{6}$$

where $P_{s\ell}$ is the set of all possible paths from s to ℓ and $w_h(p, t)$ is the accumulated edge weight of all edges in p at starting time t and w_h is the edge weighting function from equation (3).

Now we can formulate the problem to find a time with minimal heat exposure as a optimization problem with constrains:

$$\min_{t \in T} h(\ell, t) \tag{7a}$$

$$\text{s.t.} \quad t \geq t_{open}(\ell) - t_{walk}(\ell, t) \tag{7b}$$

$$t \leq t_{close}(\ell) - (t_{walk}(\ell, t) + t_{buff}(\ell)) \tag{7c}$$

$$t \geq t_{earliest} \tag{7d}$$

$$t \leq t_{latest} \tag{7e}$$

$$t \geq t_{now} \tag{7f}$$

Note, that the location ℓ is fixed, the selection of the location with lowest heat exposure is performed later in step 3. The objective function (7a) is the one defined in equation (6). The constrains (7b) and (7c) are basically ensuring that the location is arrived within the opening hours. We must ensure that the shop can be reached before it closes, therefore we have to consider the time needed to walk to the location ℓ ($t_{walk}(\ell)$) as well as the time needed perform e.g. the purchase ($t_{buff}(\ell)$). On the other hand, it can make sense to start early in the morning arrive the location ℓ just in time when its opening, so we are subtracting the walking time from the opening time. The constrains (7d) and (7e) are an earliest respectively latest point in time desired by the user and can be omitted. Finally, the last constrain (7f) guarantees, that the optimal point in time is in the future. Another thing to notice is, that the walking time $t_{walk}(\ell, t)$ depends on the starting time t, because conditional on the time a different (properly longer) optimal route can be selected.

2.2.2 Optimization

Now we must find the optimal point in time for each location $\ell \in L$. Since, not necessarily derivations for the objective function $h(\ell, t)$ exits, we have to use optimization method without derivatives like Brent's method (Brent 2002). Brent's method is a procedure for the approximation of local optima within an interval $[x_1, x_2]$, which usually converges faster than the bisection method (Press et al. 1992).

In order to apply Brent's method, we have to transform the constrains (7b) – (7f) to a lower and upper limit of an interval. The constrains (7b), (7d) and (7f) can be easily converted to a lower limit, as follows:

$$t_{lower}(\ell, t) = \max\left\{t_{open}(\ell) - t_{walk}(\ell, t), t_{now}, t_{earliest}\right\}. \tag{8}$$

Alike, we can transform the constrains (7c) and (7e) to an upper limit:

$$t_{upper}(\ell, t) = \min\left\{t_{close}(\ell) - (t_{walk}(\ell, t) + t_{buff}(\ell)), t_{latest}\right\}. \tag{9}$$

It's simple to recognize, that the interval $[t_{lower}(\ell, t), t_{upper}(\ell, t)]$ preserves the constrains from the optimization problem defined above in equation (7).

However, Brent's method can still not be applied, since the lower and upper limit of the interval is depending on the starting time t and therefore not static as required for Brent's method. That's the case because depending on the starting time a different route with minimal heat exposure, can be selected. As solution to avoid this problem we are proposing the introduction of a penalty term:

$$h'(t, \ell) = \begin{cases} h(t, \ell) & \text{if } t_{open}(\ell) - t_{walk}(\ell, t) \leq t \leq t_{close}(\ell) - (t_{walk}(\ell, t) + t_{buff}(\ell)), \\ h(t, \ell) + c & \text{otherwise,} \end{cases} \tag{10}$$

where c is a large constant such that $h(t, \ell) + c$ is never selected as optimal solution, if the constrains are violated. Now, we can use the walking time $t_{walk}^{shortest}(\ell)$ for the shortest route for the lower and upper limit. Finally, we can formulate the optimization problem for Brent's method as follows:

$$\min_{t \in T} h'\ell, t) \tag{11a}$$

$$\text{s.t.} \quad t \geq \max\left\{t_{open}(\ell) - t_{walk}^{shortest}(\ell), t_{now}, t_{earliest}\right\} \tag{11b}$$

$$t \leq \min\left\{t_{close}(\ell) - \left(t_{walk}^{shortest}(\ell) + t_{buff}(\ell)\right), t_{latest}\right\}. \tag{11c}$$

Now we can use Brent's method to find for each location ℓ the optimal point in time t^*. To avoid, that the Brent optimizer is trapped in a local optimum, its executed several times with different random start points.

3 Evaluation

3.1 Data Sets

As map data, we've used the data of the OpenStreetMap (OSM) project (OSMF 2016). Apart from the road network the data set contains for instance points of interest like shops (supermarkets, bakeries, etc.) or amenities (pharmacies, toilets, etc.). Many of them are tagged with useful information e.g. on the accessibility (e.g. `wheelchair=yes`) or their opening hours (e.g. `opening_hours="MoSa 07:00-24:00; Su,PH off"`).

We used two different kind of weather data: the hourly air temperature and relative humidity values of a weather station alongside with to data sets of a thermal scanner flight.

The hourly air temperature and relative humidity values are originating from the weather station of the German Weather Service (Deutscher Wetterdienste, DWD) in Rheinstetten near Karlsruhe (Deutscher Wetterdienst 2016). Because only the hourly values have been available, the intermediate values haven been obtained using linear interpolation of the two adjacent values.

The other kind of data that we've used, have been remote sensing data of a thermal scanner flight provided by the Nachbarschaftsverband Karlsruhe (NVK). The data set consists of two scans, on recorded in the morning and on recorded in the evening of the 26 September 2008. The data are covering an area of $25\,805\,\mathrm{m} \times 39\,555\,\mathrm{m}$ (EW NS) an have a resolution of $5\,161 \times 7\,911$ pixels (pixel size m). The measured surface temperature is in the range of $-1.7\,°\mathrm{C}$ to $18.3\,°\mathrm{C}$ (morning and evening). Before we used the data we rectified them using thin plate splines and cropped them to the same areas as the OSM data. The average surface temperature of the cropped data sets has been $4.18\,°\mathrm{C}$ (morning) respectively $11.24\,°\mathrm{C}$ evening.

3.2 Data Preparation

3.2.1 Routing

Before extracting the road network, we cropped the OSM data set to the evaluated area. Afterwards, all ways tagged with `highway`, `railway=platform` or `public_transport=platform` have been extracted.

To compute the edge weights as described above in section 2.1.2 we need to make some assumptions. That's because the weather data that we've used lacked either an appropriate spatial resolution (data of one weather station) or the required temporal resolution (only two thermal scans). So, we've assumed that the actual spatial variation of the temperature conforms with the spatial variation of the thermal scans (deviation from the mean value). Because for the relative humidity no further data have been available, we assumed that there subject of any spatial variation. For the temporal variation, we've assumed that the temporal variation in the examined area correspond to the temporal variation measure at the weather station in Rheinstetten. Additional we've used the thermal scan recorded in the morning for the time between 00:00 and 11:59 and the scan recorded in the evening for the time between 12:00 and 23:59.

So, we computed the air temperature at time $t \in T$ for the raster cell c_{ij} as follows:

$$T_a(t, c_{ij}) = \begin{cases} T_a^{station}(t) + \delta_{ij}^{morning} & \text{if } 0 \leq t < 12, \\ T_a^{station}(t) + \delta_{ij}^{evening} & \text{if } 12 \leq t < 24, \end{cases} \tag{12}$$

where $T_a^{station}(t)$ is the air temperature measured at the weather station at time t and $\delta_{ij}^{morning}$ respectively $\delta_{ij}^{evening}$ is the deviation of the raster cell c_{ij} from the mean of all raster cells from the morning respectively evening scan.

To compute an approximation of Steadman's heat index we used the formula published by Stull (2011, p. 77). Since the heat index is only defined for an air temperature between 20 °C and 50 °C we've used the air temperature as a fallback, if the air temperature was not within that range. Additionally, should be noted that if the air temperature respectively the heat index dropped in a raster cell below a comfort threshold $T_a^{comfort}$ or $T_{HI}^{comfort}$, then that comfort value has been used, because temperature below this threshold are not considered harmful. For both $T_a^{comfort}$ or $T_{HI}^{comfort}$ we used 20 °C as a threshold because temperatures above can cause a light heat stress (Staiger, Laschewski, and Grätz 2011).

For the actual implementation of the routing we used the GraphHopper framework for Java (GraphHopper GmbH 2016a; GraphHopper GmbH 2016b).

3.2.2 Optimal Time

To find an optimal point in time we used the procedure described in section 2.2. As data we used the OSM data as well, because they contain the information necessary, i.e. points of interest with associated opening hours.

For the nearby search, we're using a list of selected OSM tags like `shop=supermarket` or `amenity=pharmacy` as a search criteria. We also only considering locations which have opening hours specified (via the `opening_hours` tag). Additionally, only locations which are in a defined radius around the starting point are considered, at this we used the direct distance ("as the crow flies"). To reduce the computation effort a maximum number of results k can be specified.

As optimization algorithm, we used implementation of Brent's method in the Apache Commons Mathematics Library (ASF 2016) with 10 random start points to reduce the risk that only a local optimum is found.

If a shop is not opened over lunch, then for every time window (e.g. 9:00–13:00 and 14:00–18:30) an optimal time is determined and accordingly the solution with lowest heat exposure is used.

	temperature	heat index
Reduction of heat exposure (% of cases)		
overall	79.70 %	80.53 %
more then 5 %	42.72 %	45.11 %
more then 10 %	13.81 %	16.07 %
Reduction of heat exposure		
average	4.63 %	4.69 %
maximum	25.97 %	26.17 %
Increase of distance		
average	5.59 %	5.76 %
Reduction of relative heat exposure (w_h/w_d)		
average	2.12 °C	2.32 °C

Table 1: Overview of the results of the routing approach. The values are relative to the shortest route. The relative heat exposure is a with the distance weighted average of the thermal comfort measure. That means, on average the heat exposure was about 2 °C lower compared to the shortest route.

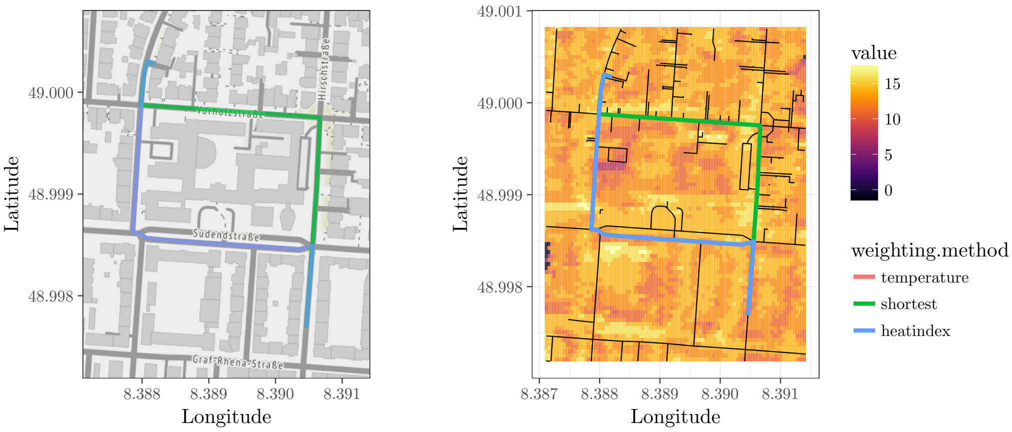
3.3 Results

3.3.1 Routing

To evaluate the routing, we've selected 1000 random pairs of start and destinations points form the examined area and 10 random dates from the period of 1 June to 31 August 2015. For each of the start destination pairs and each date we've performed the evaluation at 7:00, 11:00, 15:00, 19:00 and 23:00, so overall we had 50 000 samples. As edge weighting we've used the air temperature (equation (4), *temperature*) and the heat index (5), *heatindex*). For comparison, we computed for each sample the shortest path.

An overview of our results is given in table 1. In many cases the heat exposure could be reduced. On average the heat exposure has been decreased by 4.63 %/4.69 % while in the same time the distance was increased by 5.59 %/5.76 % on average. In some cases the heat exposure could be reduced by up to 25 %. The weighted average of the thermal comfort measure could be reduced by about 2 °C on average. There are only slight differences between the air temperature and the heat index as measure for thermal comfort.

In the example given in figure 2 the heat exposure could be reduced by 17.64 % (*temperature*) and 18.76 % (*heatindex*), while at the same time the distance only increased by 0.53 %.



(a) map

(b) thermal scan (evening)

Figure 2: Routing example: both the *temperature* and the *heatindex* weighting found the same route. (Map tiles by Stamen Design (2017), under CC BY 3.0[1]. Map data by OSMF (2016), under ODbL[2])

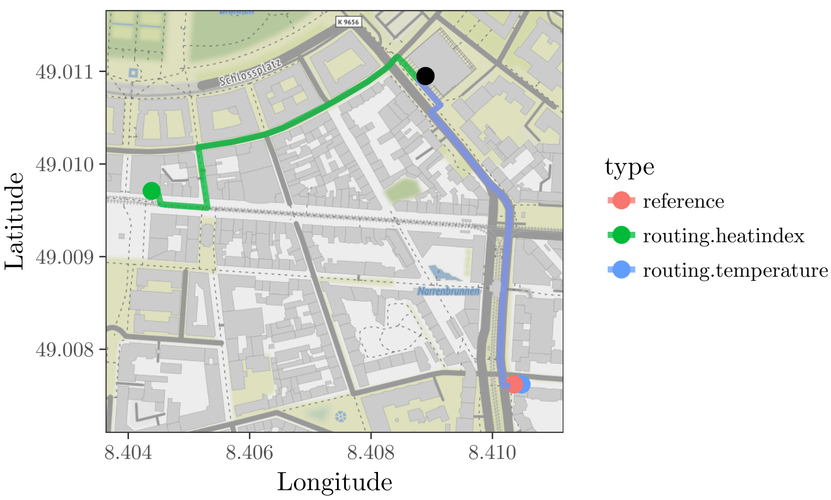


Figure 3: Example for nearby search: In the graphic the starting point (black dot) as well as the locations ranked first by the respective method. (Map tiles by Stamen Design (2017), under CC BY 3.0. Map data by OSMF (2016), under ODbL)

	temperature	heat index
Reduction of heat exposure		
% of cases	68.43 %	71.08 %
Reduction of heat exposure		
average	8.09 %	7.73 %
maximum	62.29 %	62.88 %
Increase of distance		
average	4.60 %	4.72 %

Table 2: Overview of the results of the combined approach each compared with the reference solution.

3.3.2 Optimal Time

For the evaluation of optimal time finding procedure we selected 750 random start points. One of the following four search criteria has been assigned to each of the start points at random: supermarket, bakery, chemist or pharmacy. For each of the start points a random start time t_{now} has been selected from the period of 8:00 to 20:00. The radius has been set to 1000 m for all start points and the maximum number of results has been set to 5. Additionally, for all start points a time buffer t_{buff} of 15 minutes has been assumed.

As a reference solution, we've used the closest location found during the nearby search, computed the shortest path from the starting point to this location and evaluated the heat exposure at time t_{now}. The evaluation is performed only for the locations with rank 1, because those have the lowest heat exposure.

The results for the combined approach are given in table 2. Here the average reduction compared to the routing approach is significantly higher. That is what we expected, because the heat exposure can vary strongly with the time of the day. On the other hand in less case a improvement compare to the reference solution has been found.

In the example given in figure 3 the *temperature* weighting selected the same pharmacy and optimal point in time (9:27) as the reference solution. Contrary the *heatindex* routing selected a different pharmacy which is 476.6 m instead of 434.5 m a way from the starting point. Additional the method found a different optimal time (19:39) and those the heat exposure could be reduced by 18.49 %.

[2] `http://creativecommons.org/licenses/by/3.0`
[2] `http://www.openstreetmap.org/copyright`

4 Conclusion

In this work, we proposed a two step approach to reduce the heat stress for individuals. We achieved this goal by creating a decision support system that computes heat-optimal paths to locations as well the optimal points in time to do so. We evaluated this on typical every-day activities such as grocery shopping. We showed that our approach reduces the heat stress in a vast majority of the cases. On average the heat stress can be reduced by 4.7% while the trade off in additional distance is also quite low. This is never more than 5.76 % . We achieved these results, contrary to the existing work, for relatively small distances which average over 2 km. The impact of these results are simple, but significant. One can easily compute our approach and decide for themselves the trade-off between additional distance and the heat stress reduction. Thanks to the very small assumptions on the data set, one can apply the approach quite easily to other cities. But these assumptions are also the main restriction of this work. Given the rise of smart cities and and (hopefully) more available data sources, one could improve the approach with more fine-detailed data. Even more interesting would be the inclusion of intra urban temperature forecasts. By incorporating exact forecasts of future values along possible pathways, the optimal point in time as well as the reduction of the heat stress could be improved. Additionally the inclusion of more complex heat indices could increase the validity for any potential user. Finally, the computation of an overall route which covers a multitude of potential points of interests would be an interesting extension. This could be used for tourists or even worker scheduling. Here not only the time and the route with minimal heat exposure should be considered but also, the ordering of the locations.

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