Predicting Volunteer Travel Time to Emergencies

Tobias Andersson Granberg
Linköping University
tobias.andersson.granberg@liu.se

Sara Erlander
Linköping University
sarer203@student.liu.se

David Fredman
Heartrunner
david@heartrunner.com

Lovisa Olovsson
Linköping University
lovol969@student.liu.se

Emma Persson
Linköping University
emmpe397@student.liu.se

ABSTRACT

A model is developed, which can predict the travel time for volunteers that are dispatched as first responders to emergencies. Specifically, the case of lay responders to out of hospital cardiac arrest is studied. Positions from historical responses is used to estimate the real response times, which are used to train and evaluate the new travel time model. The new model considers the road network and the transport mode most likely used by the volunteers. The results for the new model are compared to a model used in an existing volunteer initiative. They show that the new model can make better predictions in 59.7% of the cases. This can be used directly as a base for improving the travel time estimates in existing volunteer initiatives, and to improve the input data to the continuously evolving volunteer resource management systems.

Keywords

Travel time modelling, Lay responder dispatch, Out-of-hospital cardiac arrest, Decision support, First response, Volunteer responders

INTRODUCTION

There is a growing interest and increasing number of initiatives for utilizing volunteers as additional resources in emergency situations (Valeriano et al. 2021). This is a low-cost solution that may have a huge impact, leading to saved lives and property, especially if utilized properly. In the current guidelines on cardiopulmonary resuscitation (CPR) from the European Resuscitation Council, introduction of systems that alert volunteers to suspected cardiac arrests are advocated (Semeraro et al. 2021). However, one major challenge in the management of volunteer resources, e.g., compared to professional resources, is the additional uncertainty associated with these resources (Matinrad et al. 2021). Since they are volunteers, typically they may not be obliged to respond when receiving a mission, and there is additional uncertainty regarding what they will do, when they will do it, and the impact of what they are doing. The response time, i.e. the time from when an alert has been sent to a volunteer, until (s)he has arrived at the incident site, is one important component contributing to this uncertainty. Most often, the largest part of the response time is the travel time. One way to estimate this, which is used in some volunteer initiatives today, is to take the Euclidean (straight line) distance and divide this with an estimated travelling speed (Berglund et al. 2018). While this may work sufficiently under some conditions, if there exist barriers, like large roads, rivers, or house blocks on the way, it will severely underestimate the travel time. Also, it does not take into account that the travel distance and speed may vary depending on different modes of transportation (i.e., on foot, bike, car) or the road network layout. Good travel time estimations are important for volunteer management purposes, e.g. when selecting which volunteers to dispatch or when doing task allocation, since an evaluation of a potential decision might be misleading if the response times are poorly estimated. Furthermore, for the volunteers, it is aggravating to be sent to incidents they may not be able to reach in time.

The aim is to develop and validate a travel time model for volunteers that considers the road network, barriers, and different modes of transportation.

As a case, we use the Heartrunner initiative in Sweden, where volunteers sign up for receiving alerts on nearby out of hospital cardiac arrests (OHCA). When this occurs, an alert is sent to the 30 volunteers closest to the patient, within a given radius, and these are tasked to either go directly to the patient to start CPR, or to first pick up automated external defibrillator (AED), and then travel to the patient. This is further described in the section HEARTRUNNER, which comes after a brief overview of RELATED WORK.

Using data from volunteer responses, we find out which volunteers reached the patient, and then estimate their real travel times. These are then used to develop and test the new travel time model. This is described in detail in the sections INPUT DATA and A NEW TRAVEL TIME MODEL. Finally, the new model is compared to the Euclidean distance-based model in the section RESULTS AND ANALYSIS. The paper ends with CONCLUSION, where we also outline some paths for future research.

RELATED WORK

Volunteers are important resources in both disasters and more frequent emergencies. Unaffiliated (spontaneous) volunteers offer serious challenges in terms of resource management, since they first must be registered and assessed before it is possible to know how to use them best. Thus, effective coordination of these volunteers is vital, something that has been addressed by Meissen et al. (2017) and Rauchecker and Schryen (2018). While both of these work concern larger events like disasters, another type of initiative that has expanded quicky the last couple of years is using volunteers as first responders to out-of-hospital cardiac arrest (OHCA), i.e. a type of daily emergency. These volunteers are typically dispatched to an OHCA through their mobile phones. In a review, Valeriano et al. (2021) identified 25 unique technologies, from 15 different countries for this. Another example of a program employing volunteers is the Enhanced Neighbor initiative where civilians in rural areas and villages with a poor emergency services coverage are alerted to fires, cardiac arrests and traffic accidents (Ramsell et al., 2017).

In many of the volunteer initiatives, it is necessary to determine which task that should be done by which volunteer to obtain the best possible outcome. Several researchers have addressed this, including Falasca and Zobel (2012), Lassiter et al. (2015), Khalemsky and Schwartz (2017), and Matinrad et al. (2021). The first two works focus on (post) disasters and the last two on daily emergencies. If the response time has any impact on the outcome, which is usually the case in both disasters and daily emergencies, a good prediction of the expected response time for the volunteers is necessary; a major part of the response time is usually the travel time. While travel time modelling for emergency services has a long history, it is mostly focused on road vehicles, like in Kolesar et al. (1975) where a model for fire engines travel times as a function of the travel distance is presented, or Budge and Ingolfsson (2010) and Westgate et al. (2016), who analyze ambulance travel times. While it is challenging to account for uncertainty in the travel time, this has become an active area of research, and the number of models offering travel time estimates for regular type of traffic (personal cars) is growing (Jula et al. 2008). As an example, Jenelius and Koutsopuolus (2013) present a statistical model for travel time estimations, and show that factors affecting the estimate includes the season, the level of congestion and the weather as well as link attributes like the number of lanes, traffic signals and speed limits.

Studies for other modes of transport, within emergency response, is scarcer, but Jonsson et al. (2020) determine and analyze the traveling speed for lay responders to OHCA. Using a similar methodology to the one we employ in this paper, they analyze historical positions of dispatched volunteers, and conclude that the mean travelling speed varied between 1.8 m/s in densely populated areas to 3.1 in the least populated areas, with an overall mean speed of 2.3 m/s.

Compared to Jonsson et al. (2020) and other previous studies, we (to the best of our knowledge) present the first road network-based travel time model for volunteers to daily emergencies that consider the transport mode, and that can be used to predict the travel time before making task assignments and dispatching the volunteer. This can be used directly as a base for improving the travel time estimates in the currently active volunteer initiatives, and to improve the input data to the continuously evolving volunteer resource management systems.

HEARTRUNNER

The Heartrunner initiative started as the research project “SMS lifesavers”, by Karolinska Institutet in Sweden in 2010. The idea was to see if it was possible to initiate early bystander CPR, by alerting nearby volunteers by SMS (Ringh et al. 2011). This proved to increase bystander CPR significantly, as shown in a randomized controlled trial, alerting volunteers to suspected OHCA in Stockholm, Sweden (Ringh et al. 2015). The volunteers were later alerted through a smartphone app and a subset of the volunteers were instructed to bring an AED to the patient (Berglund et al. 2018). One of the latest developments are investigating the possibility to use drones to transport the AED to the patient (Schierbeck et al. 2021). Since transferring from a research project to an integrated part of Swedish emergency response in 2016, the project is run by the company Heartrunner Sweden AB (https://heartrunner.com/), with currently (November 2021) over 100 000 volunteers in Sweden and over 130 000 in Denmark where the whole country is covered by the system.

When a cardiac arrest occurs, a request is sent from the emergency dispatch center to volunteers in the area to help. The volunteers can either be asked to go directly to the patient and start CPR or to go and pick up an AED before going to the patient. The request is sent to a maximum of 30 volunteers, the ones closest to the patient according to their latest position update, and within 1320 meters.

Figure 1 visualize the concept. The green volunteers within the red circle are the ones that get a request to help the patient. The orange volunteers which are outside the circle are too far away from the patient and are therefore not alerted.

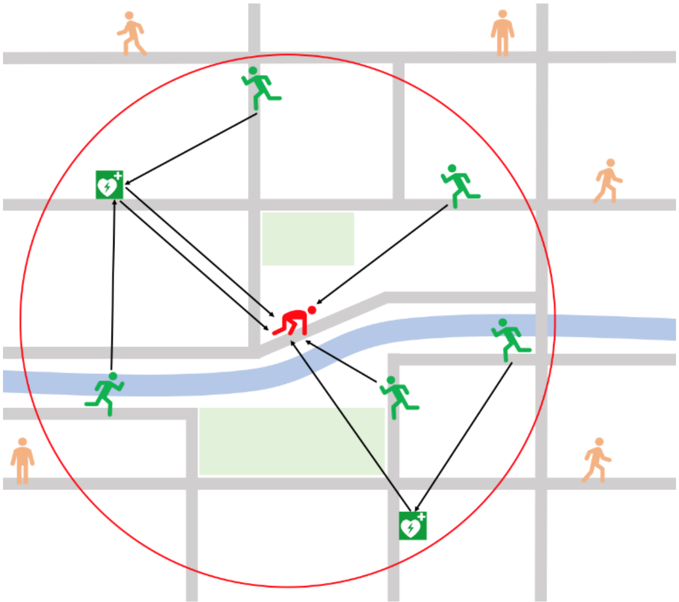

Figure 1. An overview of the Heartrunner concept

In the current system, the travel time for a volunteer is estimated as the Euclidean distance divided by a speed of 2 m/s. As illustrated in Figure 1, the Euclidean distance from the volunteers to the patient does not consider barriers such as rivers or the need to follow links in the road network, which may result in misleading estimates of the travel times.

INPUT DATA

Data characteristics

Historical data on volunteer responses during the period 2019-08-31 until 2020-10-04, for the Stockholm and Västra Götaland regions in Sweden was used. These were assignee reports, with time stamps and position data, and questionnaires filled out by the volunteers after the alert. The assignee reports contain incident id, incident position, incident time, volunteer id and alias and position and time updates for the volunteers. Data that was collected from questionnaires are mission id, alias, if the volunteer reached the indicted location, if they tried to get an AED and which travel mode that was used. The travel modes that the volunteer could choose from was walking, bicycling, motor vehicle or emergency response vehicle.

From the reports, it is possible to get relevant information about which travel mode each volunteer used, which can be combined with the position updates. From the questionnaires, the volunteers that reached the patient was selected, and only volunteers that stated that they did not pick up an AED was included in the data for further calculations. The reason was not to have to include the time to find and pick up an AED in the model.

Standard cleaning of the data was performed, e.g. removing volunteer paths that were 100% longer than the shortest equivalent route in the road network, or when it was not possible to accurately determine start and stop positions for the volunteers.

From 49 111 volunteer dispatches in the data, 1509 volunteers stated that they reached the patient. From these, it was possible to extract 651 cases that fulfilled the cleaning criteria. There are five different travel modes: walking, bicycle, driving, ambulance, and firefighter/police, where the two latter are when professional personnel use the app while on duty. From these, two categories were created: walking/bicycling and driving. Due to the low number of volunteers answering "bicycle," this data was merged with that of the volunteers travelling by foot in the category walking/bicycling. There was also a low amount of data for the firefighters/police on duty and ambulance personnel, so these were merged with the data for the volunteers that arrived by car in the category driving.

We divided the data into two equally sized sets; one to train (N=326) and one to evaluate (N=325) the model. The sets were divided so that they included as much data from the Stockholm region as from the Västra Götaland region, and equally distributed over travel mode category and time.

Calculating real travel times

We used the historical data to calculate estimates of the real travel times for the volunteers, starting by selecting start and stop positions. The first set of position updates before the volunteers have started moving towards the patient needs to be excluded from the total distance and total time for the volunteers' journey. This to exclude the call-out time (the time from alert until the volunteer starts travelling towards the incident site). To identify these, a threshold value was set for both the initial position updates and the final position updates in the volunteer path. Once the volunteer gets a position which is more than the threshold from the initial position, (s)he is assumed to have started the journey. The start position can then be set to the previous position update before the volunteer have exceeded the threshold radius (see Figure 2, where position 2 is selected as the start position).

The stop position is selected in the same way as the start position but with the patient position as the reference point. An example path including the position updates are shown in Figure 2. The stop position is set to the second position update which is less than the threshold value from the patient.

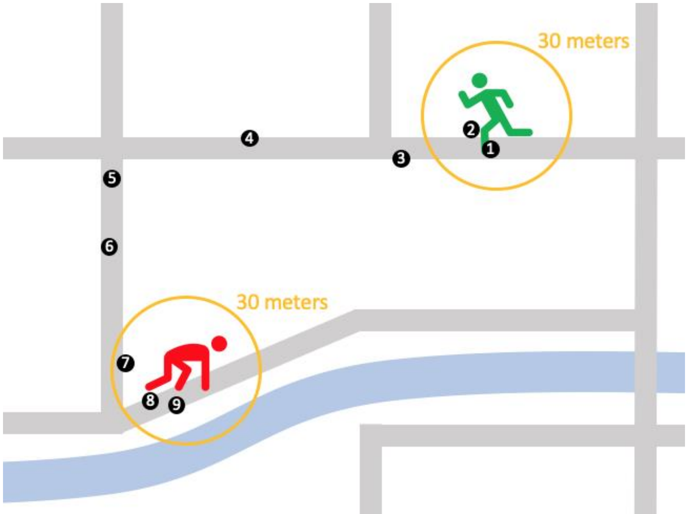

Figure 2. The choice of start and stop positions

Figure 2 presents a visualization of a case where the volunteer travels by foot to a patient, using the road network. The start position is set to 2 for the volunteer since position update 3 is outside the threshold, and position 1 is the reference point. The stop position is set to 8 since the volunteer is within the threshold radius from the patient and the previous position update, update 7, is also within the threshold radius from update 8.

If the threshold value is set to a small value, the volunteer must get closer to the patient position to get a stop position. Thus, if the volunteer decides to press the arrival button in the application before they arrive within the radius of the threshold value, this data will be excluded. Another consequence is that the volunteer path might never reach the patient position due to the positioning error. A large threshold value results in less reliable data, including start positions where the volunteer has not begun their journey yet and where there is a stop position even though the volunteer has not reached the patient yet.

Table 1. Amount of Data in Relation to Threshold Value

Threshold value	Total rows of data
45	718
30	651
15	452

Table 1 presents the amount of data obtained when setting the threshold value to 45, 30 or 15 meters. As can be seen, the amount of data is strongly correlated to the threshold value. There is approximately a 37 percent decrease in rows of data when decreasing the value from 45 to 15 meters.

Figure 3 visualize the start of one volunteer path with a threshold value of 15, 30 and 45 meters. The axes represent the coordinates in longitude and latitude where the rings marked in the figures are position updates. The cross marked in the upper right corner is the position when the volunteer receives the request, i.e. the initial position. The green rings represent the position updates included in the volunteer path when calculating the real travel time. The red circles are position updates which are not included in the path, depending on the threshold value. If a circle is red, it means that the threshold value, in this case for the start position, is not fulfilled yet.

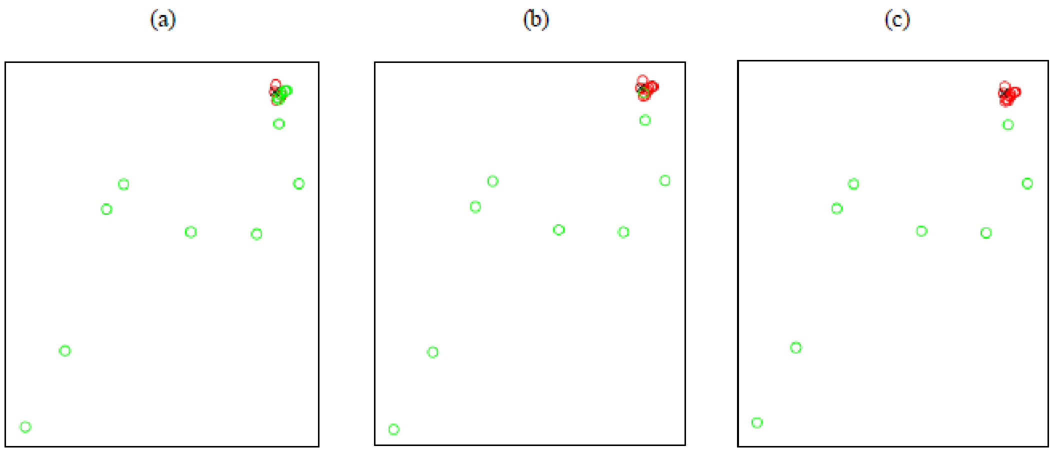

Figure 3. The start of one volunteer's path with a threshold value of (a) 15 meters, (b) 30 meters and (c) 45 meters

The cross and the first green position update which is closest to the cross can be analyzed by comparing Figure 3a, 3b and 3c. Figure 3a includes several green circles in the same area, at the cross, while Figure 3c does not have any green circles nearby the cross. Figure 3b, with 30 meters threshold value, has only one green circle in the near area of the cross. This means that Figure 3a, with a threshold value of 15 meters, includes position updates before the volunteer has started the journey which will lead to a longer real travel time than the actual time for the journey. Figure 3c results in a too short travel time since the threshold value of 45 meters is too high to register a position update near the initial position update. This means that to calculate a real travel time as accurately as possible, in this case, the threshold value should be between 15 and 45 meters. Further similar analysis, varying the threshold value, resulted in the conclusion that 30 meters is a good value to use.

After selecting the start and stop positions, the travel time was determined by taking the difference between the times stamps for the stop and the start position. The travel distance for each volunteer is the sum of the distances traveled from each position update, starting from the start position until the stop position. The positions were given in longitude and latitude, and the Haversine formula was used to calculate the distance between two positions. The velocity for each volunteer was calculated by dividing the distance with the real travel time. This gave us estimated truths (distances, speeds and travel times) that were used to train and to evaluate the new model.

A NEW TRAVEL TIME MODEL

To develop a new travel time model, a set of possible input parameters were considered. Analysis was conducted regarding e.g. time of day or if the travel time differs between urban or suburban areas, without finding any clear correlations. Thus, the final travel time model considers the road network, the choice of travel mode and the fact that a volunteer that is walking or bicycling has the possibility to take shortcuts. The road network, based on Bing

Maps (https://www.bing.com/maps/) is used to calculate the road distance that the volunteer must travel to reach the patient. This enables the consideration of several types of barriers, such as houses and rivers. The travel mode is taken into consideration since it affects the velocity of the volunteer. Bing Maps calculates the walking distance based on a network for pedestrians, but this does not consider other possible routes that are not included in the network. One example of this is the case when it is possible to take a shortcut through green areas. For the training data, the walking distances calculated by Bing Maps are in general 4.6% longer than the real volunteer distances for walking/bicycling. Therefore, a shortcut factor is included in the model to compensate for the fact that a volunteer that is walking or biking has the possibility to take shortcuts.

Figure 4, 5 and 6 shows the relationship between the (calculated) velocity and the (calculated) travel distance for the cases in the training data for the categories walking/biking and driving and for the general case where all travel modes are included. The dots represent the cases in the training set and the line is the least squares regression line of the cases in the training set. In the figures, the function of the least squares regression line is also presented, where y is the velocity of the volunteer and x is the travel distance.

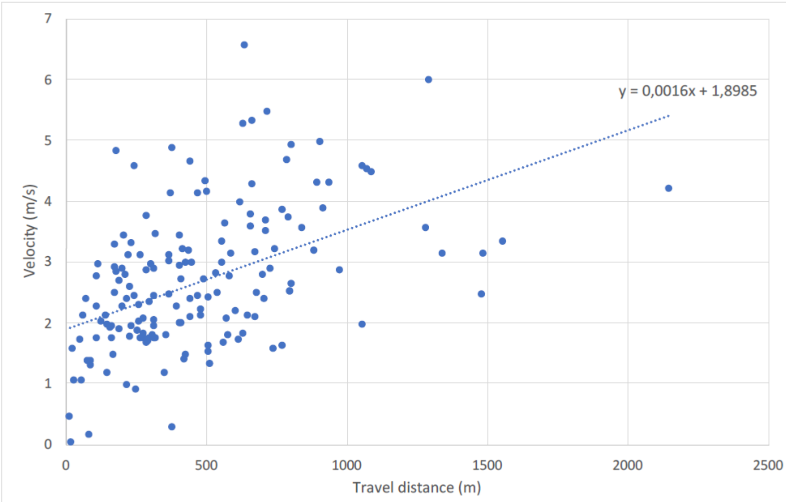

Figure 4. The relationship between velocity and travel distance for walking/biking (N=160, R^2=0.23)

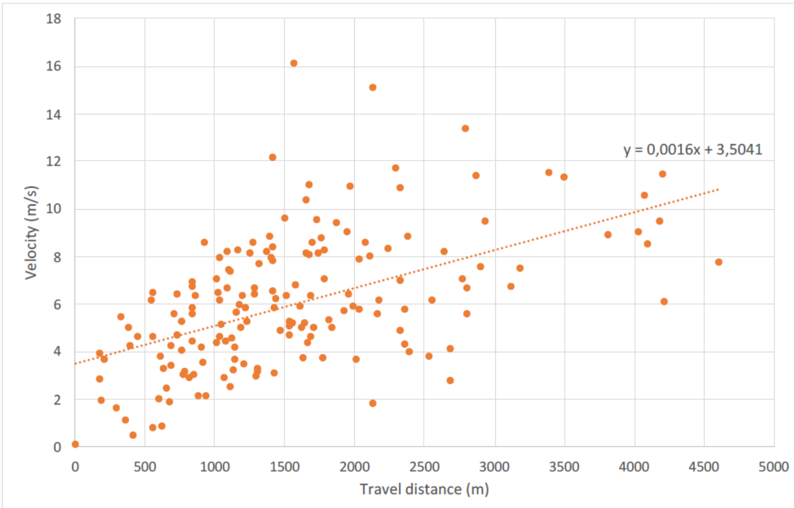

Figure 5. The relationship between velocity and travel distance for driving (N=166, R^2=0.27)

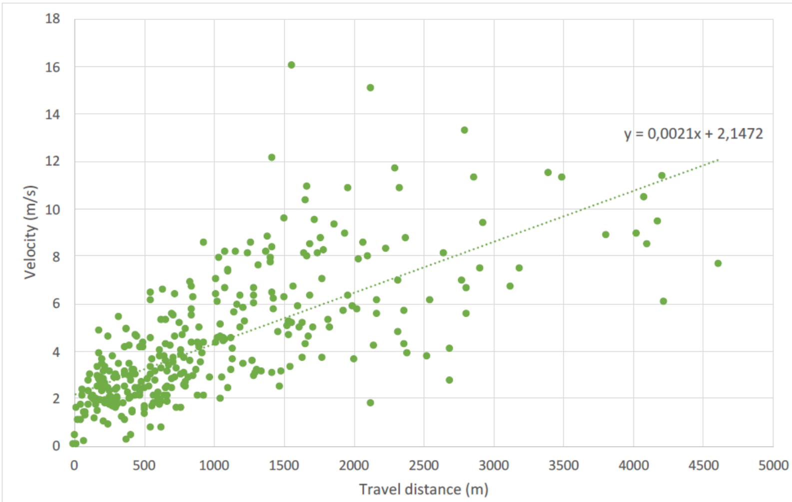

Figure 6. The relationship between velocity and travel distance for all travel modes (N=326, R^2=0.49)

When dispatching a volunteer, the travel mode that (s)he will use is not known. Thus, the travel time model first needs to predict the travel mode. Figure 7 presents a boxplot of the travel distance for the different travel modes in the training data. The filled areas, within the boxes, are used to decide the intervals for the distances which corresponds to walking/biking or driving mode. The line in each box marks the median value and the cross marks the mean value. The minimum value is marked with a vertical line below the boxes while the maximum value is marked above both boxes where the samples over the maximum are extreme values in the data set.

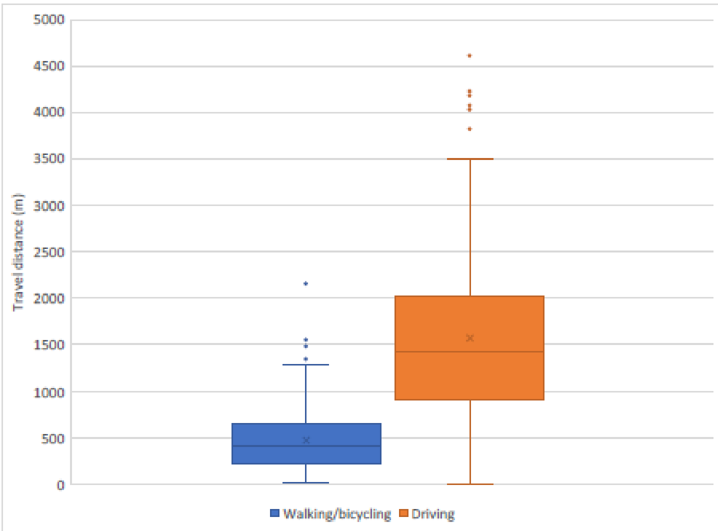

Figure 7. Boxplot of travel distance for walking/biking and driving mode

Based on the data illustrated in Figure 7, it is assumed that the volunteer uses the walking/biking mode when the travel distance is less than 662 meters. Then, Bing Maps is used to suggest the shortest walking path from the start to the stop position, and the velocity is set to the value given by the regression function for walking/biking (Figure 4). The distance is also shortened by the calculated shortcut factor. If the distance is 915 meters or longer, the volunteers are assumed to be traveling by motor vehicle, and therefore Bing Maps driving distance and driving velocity (Figure 5) is used. If the distance is between 662 and 915 meters, it is uncertain which travel mode the volunteer is most likely to use. In these cases, the travel distance is set to Bing Maps driving distance since, in general, it is a better fit to the real distance in comparison to the walking distances from Bing Maps. For the velocity, the regression value for all travel modes (Figure 6) is used. Finally, the estimated travel time is calculated by dividing the distance by the velocity.

Thus, the calculations made are:

$$Distance = \begin{cases} \dfrac{Bing\ walking\ distance}{1.046}, if\ Bing\ walking\ distance\ \leq 662\ m \\ Bing\ driving\ distance, if\ 662\ m\ \leq Bing\ walking\ distance\ \leq 915\ m \\ Bing\ driving\ distance, if\ Bing\ walking\ distance\ \geq 915\ m \end{cases}$$

$$Velocity = \begin{cases} 0.0016 \cdot Distance + 1.8985, if\ Bing\ walking\ distance\ \leq 662\ m \\ 0.0021 \cdot Distance + 2.1472, if\ 662\ m\ \leq Bing\ walking\ distance\ \leq 915\ m \\ 0.0016 \cdot Distance + 3.5041, if\ Bing\ walking\ distance\ \geq 915\ m \end{cases}$$

$$Travel\ time = \frac{Distance}{Velocity}$$

RESULTS AND ANALYSIS

Main results

The performance of the developed travel time model is evaluated by comparing it to a Euclidian distance-based model (EBM), where the distance between the start and stop positions are calculated using the Haversine formula, and a mean velocity of 2 m/s is used. Real travel times are calculated for all cases in the evaluation set (N=325), and estimated travel times are calculated for the Euclidian model and the new route-based model (RBM). Due to the simple calculations required, both models provided travel times instantly during the tests; however, using an external supplier like Bing for the routes, means there is risk for delays in getting the required data, e.g. due to network failure or server overload. The three performance indicators used are:

1. ME [s], which is the mean error in the travel time estimation compared to the real travel time.
2. MAE [s], which is the mean absolute error.
3. Improvement [%], which is the share of cases when the RBM has a smaller MAE then the EBM.

The result is presented in Table 2, where statistical measures are given before the performance indicators. These are given for the evaluation set, i.e. 325 cases, where the estimated real mean travel time was 234.5 seconds. This seems to be slightly overestimated by the EMB (275.7 s) and underestimated by the RBM (205.3 s). While the RBM makes a pretty good job of estimating the real distance, the EBM naturally has a much shorter distance, which is compensated by the slower mean speed that is used to calculate the travel time. The real travel speed is 4.4 m/s, but this depends on the travel mode. Looking at cases where volunteers went by foot, the real mean travel speed is 2.5 m/s, for bike 3.4 m/s and for car 6.1 m/s. This is interesting to compare to the results of Jonsson et al. (2020) who found a mean travel speed of 2.3 m/s for all travel modes, which is less than 4.4 m/s. This may be due to how the start and start positions are selected, where Jonsson et al. (2020) selected the start position when the volunteer accepted and the stop position when (s)he was within 25 meters from the patient position. As we use a radius also for the start position, we will eliminate any time spent e.g. getting out from a building, accessing a vehicle etc. Thus, it is not surprising that the mean speed we obtain is higher than the one in Jonsson et al. (2020).

Table 2. Comparing the travel time models

	Real	EBM	RBM
Mean travel time (s)	234.5	275.7	205.3
Mean distance (m)	1009.9	551.4	1046.5
Mean speed (m/s)	4.4	2.0	4.3
ME (s)		41.2	-28.8
MAE (s)	-	124.6	87.4
Improvement (%)	-	-	59.7

Regarding the performance indicators, as can be seen in Table 2, the overestimation of the EBM is visible in the mean error, just like the underestimation by the RBM. The latter has a mean error closer to zero, and also a smaller variation as evident by the mean absolute error. Using the route-based travel time model, it is possible to reduce the MAE from 124.6 to 87.4 seconds, that is by 37.2 seconds, a reduction of 30%. The RBM manages to do a better travel time estimation in 59.7% of the cases, compared to the simpler, Euclidian distance-based model.

Known travel mode

If the intended travel mode of the volunteer is known, it should be possible to further improve the travel time estimation. This information is difficult to get in practice as it might involve having the volunteers fill it in dynamically in the app before being given a task, which is not desirable since it would delay the response. However, it is easy to check the potential of having this information, simply by including it in the RBM. Thus, instead of guessing the travel mode selected by the volunteer, this information is fetched directly from the historical data. This gives us the route-based model with known travel mode (RBM-KTM). Results from this model together with results for the other two models are shown in Table 3.

Table 3. Results including a model with known travel mode

	EBM	RBM	RBM-KTM
ME (s)	41.2	-28.8	-34.4
MAE (s)	124.6	87.4	85.7
Improvement (%)	-	59.7	59.4

As indicated in Table 3, knowing the travel mode beforehand has no major effect on the travel time estimations. Indeed, the number of times when the RBM-KTM is better than the EBM is slightly lower than for the RBM, though the difference is negligible. The mean absolute error in the travel time estimation is however slightly lower for the RBM-KTM. The mean error indicates that the RBM-KTM underestimates the travel time even more than the RBM, but it is still closer to zero compared to the EBM.

It is difficult to give a certain answer as to why there is no real improvement when including this additional information, but looking at the boxplot Figure 7, the travel modes are fairly well separated based on the distance. Thus, it is possible that the simple way of picking a travel mode based on the distance is sufficient to model this aspect, and that the lack of even a minor improvement in regard to the Improvement indicator is due to a small dataset, making the stochastic variations shine through. However, as already mentioned, since obtaining and utilizing this information would be difficult, it is promising that the travel time model works as well without it.

Improving the Euclidian based model

One very simple way of improving the travel time estimation without using a new type of model is to calibrate the EBM. In the previous tests, we used 2 m/s as the mean speed when calculating the estimate for the EBM, since this was the value used in the Heartrunner system. However, calibrating this parameter using the Excel Solver to minimize the MAE for the training set, gave a new mean speed of 2.6 m/s, thus compensating for the overestimation noticed in Table 2. This gives the model EBM-cal, and the results (for the evaluation set) in Table 4.

Table 4. Results including the calibrated Euclidian distance-based model

	EBM	EBM-cal	RBM
ME (s)	41.2	-22.4	-28.8
MAE (s)	124.6	104.5	87.4

As can be seen in Table 4, the calibrated EBM, now underestimates the travel time slightly, and has a mean error closer to zero than even the RBM. However, the MAE is still larger by 17.1 seconds, which is likely due to the ability of the RBM to take barriers, the road network and the travel mode into account. In terms of improvement, the RBM finds a better estimate in 58.2% of the cases compared to the EBM-cal.

CONCLUSION

The results show that a travel time model considering the travel mode of the volunteer and utilizing road network information is capable of better estimating the travel time from a volunteer start position to the incident site than the model currently used in the studied volunteer initiative. They also show that using historical data, it is possible to improve the estimations just using Euclidian distance and a mean speed, but then the model is still not be able to consider possible barriers.

The study highlights the difficulty of travel time estimations, that comes from all the uncertain components that is not possible to capture; people travel (walk or run, bike or drive) with different speeds, they may get delayed on the way due to e.g. congestion or taking a wrong turn. One specific example related to the OHCA volunteer context is that a volunteer travelling towards a patient will likely slow down if (s)he learns that the ambulance has already arrived but might still finish the journey and check with the ambulance personnel if (s)he can be of assistance. Thus, it will be regarded as a feasible volunteer path, but probably with a longer travel time than if the ambulance had not arrived. Other aspects that are not included in this study, but that are mentioned in previous research are for example traffic lights, speed limits, one-way streets, weather and season, hilly terrain, differences in urban, suburban and rural areas like high-rise buildings and access to buildings. At least some of these would be possible to include in the travel time estimations, and possibly try in a real-life situation, which is an interesting avenue for further research.

Another interesting aspect to consider in future research is how another method for calculating the distances than using Bing Maps would affect the time estimations. This is because different actors in the web mapping market use different road networks and other distance calculations to decide the shortest route. Alternatively, a purpose-built road/walkway network could be constructed, e.g. based on OpenStreetMap, taking into account possible shortcuts, and having specific link-based travel speed estimations. Having a local server for the route calculations would also decrease the risk for delays in getting route data, e.g. due to network congestion. Getting good travel time estimations is only valuable as long as the time for getting them is insignificant compared to the response times.

ACKNOWLEDGMENTS

This research was partly funded by the Swedish Civil Contingencies Agency (MSB), through the Center for Advanced Research in Emergency Response (CARER).

REFERENCES

Berglund, E., Claesson, A., Nordberg, P., Djärv, T., Lundgren, P., Folke, F., Forsberg, S., Riva, G. and Ringh, M. (2018). A smartphone application for dispatch of lay responders to out-of-hospital cardiac arrests. *Resuscitation*, 126, 160–165.

Budge, S. and Ingolfsson, A.Z.D. (2010) Empirical Analysis of Ambulance Travel Times: The Case of Calgary Emergency Medical Services. *Management Science*, 56, 716-723.

Falasca, M. and Zobel, C. (2012) An optimization model for volunteer assignments in humanitarian organizations. Socio-Economic Planning Sciences, 46(4), 250–260.

Jenelius, H. and Koutsopoulos, H. (2013) Travel time estimation for urban road networks using low frequency probe vehicle data, *Transportation Research Part B: Methodological*, 53, 64-81.

Jonsson, M., Berglund, E., Djärv, T., Nordberg, P., Claesson, A., Forsberg, S., Nord, A., Tan, H.L. and Ringh, M. (2020) A brisk walk - Real-life travelling speed of lay responders in out-of-hospital cardiac arrest. *Resuscitation*, 151, 197-204.

Jula, H., Dessouky, M. and Ioannou, P. (2008) Real-Time Estimation of Travel Times Along the Arcs and Arrival Times at the Nodes of Dynamic Stochastic Networks, *IEEE Transactions on Intelligent Transportation Systems*, 9, 97-110.

Khalemsky, M. and Schwartz, D. G. (2017). Emergency Response Community Effectiveness: A simulation modeler for comparing Emergency Medical Services with smartphone-based Samaritan response. *Decision Support Systems*, 102, 57–68.

Kolesar, P., Walker, W. and Hausner, J. (1975) Determining the relation between fire engine travel times and travel distances in New York City, *Operations Research*, 23, 614-627.

Lassiter, K., Khademi, A., and Taaffe, K. M. (2015). A robust optimization approach to volunteer management in humanitarian crises. *International Journal of Production Economics*, 163, 97–111.

Meissen, U., Fuchs-Kittowski, F., Jendreck, M., Pfennigschmidt, S., Hardt, M. and Voisard, A. (2017) A general system architecture and design for the coordination of volunteers for agile disaster response, *Proceedings of the 14th ISCRAM Conference*, Albi, France.

Matinrad, N., Granberg, T. A. and Angelakis, V., (2021), Modeling uncertain task compliance in dispatch of volunteers to out-of-hospital cardiac arrest patients. *Computers & Industrial Engineering*, Vol. 159.

Ramsell E, Pilemalm S, and Andersson Granberg T, (2017) Using Volunteers for Emergency Response in Rural Areas – Network Collaboration Factors and IT support in the Case of Enhanced Neighbors, *Proceedings of the 14th ISCRAM Conference*, Albi, France.

Rauchecker, G. and Schryen, G. (2018) Decision support for the optimal coordination of spontaneous volunteers in disaster relief, *Proceedings of the 15th ISCRAM Conference,* Rochester, NY, USA.

Ringh, M., Fredman, D., Nordberg, P., Stark, T., and Hollenberg, J. (2011). Mobile phone technology identifies and recruits trained citizens to perform CPR on out-of-hospital cardiac arrest victims prior to ambulance arrival. *Resuscitation*, 82, 1514–1518.

Ringh, M., Rosenqvist, M., Hollenberg, J., Jonsson, M., Fredman, D., Nordberg, P., Järnbert-Pettersson, H., Hasselqvist-Ax, I., Riva, G. and Svensson, L. (2015) Mobile-phone dispatch of laypersons for CPR in out-of-hospital cardiac arrest, *New England Journal of Medicine*, 372, 2316–2325.

Schierbeck S, Hollenberg J, Nord A, Svensson L, Nordberg P, Ringh M, Forsberg S, Lundgren P, Axelsson C, and Claesson A. (2021) Automated External Defibrillators delivered by drones to patients with suspected Out-of-Hospital Cardiac Arrest. *European heart journal*, https://doi.org/10.1093/eurheartj/ehab498.

Semeraro, F., Greif, R., Böttiger, B.W., Burkart, R., Cimpoesu, D., Georgiou, M., Yeung, J., Lippert, F., Lockey, A., Olasveengen, T.M., Ristagno, G., Schlieber, J., Schnaubelt, S., Scapigliati, A. and Monsieurs, K. (2021) European Resuscitation Council Guidelines 2021: Systems saving lives, *Resuscitation*, 161, 80-97

Valeriano, A., Van Heer, S., de Champlain, F., and Brooks, S. (2021). Crowdsourcing to save lives: A scoping review of bystander alert technologies for out-of-hospital cardiac arrest. *Resuscitation*, 158, 94-121.

Westgate, B., Woodard, D., Matteson, D. and Hendersson, S. (2016) Large-network travel time distribution estimation for ambulances, *European Journal of Operational Research*, 252, 322-333.