Towards an Intelligent Triage Bracelet: A Conceptual Study of a Semi-Automated Prehospital Triage Algorithm and the Integration of Blood Pressure Measurement

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Abstract: First responders often reach their limit when they have to find and triage dozens of victims in a mass-casualty incident. However, a delay in treatment directly affects the survival chances of seriously injured people. A method to reduce the time for the prehospital triage could potentially save lives. Hence, this work outlines the conceptual development of an intelligent bracelet that semi-automates the prehospital triage. This bracelet is supposed to enable non-professional first responders to help with the triage, which maximises the utilisation of man power at a mass-casualty incident. The bracelet should automate the part of the triage that is based on vital, position and movement data and it should guide through the necessary patient interactions. As a step towards this goal, this work proposes a semi-automated triage algorithm that is based on mSTaRT. One of the challenges to implement this concept is to measure the blood pressure with a small and easy to attach system. Therefore, this work presents a wrist worn oscillometric blood pressure measurement prototype. Furthermore, we discuss the use of machine learning methods to forecast triage level changes.

1 INTRODUCTION

After a mass-casualty incident, such as a train crash or an environmental disaster, a large number of victims immediately need emergency treatment. However, often only a few first responders are quickly available. Upon arrival, the first responders, with the necessary training, perform a comprehensive prehospital triage of all victims to categorize them depending on the severity of their injuries and consequently define the order of treatment. It is impossible to immediately treat everyone. Furthermore, a simultaneous monitoring of all patients is not realizable, hence a sudden deterioration of a patient's health can remain undetected.

Innovative technical assistance could accelerate the triage process, which saves time for victim treatment. Additionally, it makes continuous victim monitoring possible. We hypothesize that the right technical assistance enables first responders without dedicated triage training to perform a semi-automated prehospital triage. Consequently, this would maximize the utilisation of man power at a mass-casualty incident.

To develop a semi-automated prehospital triage concept we first analysed which part of the *modified Simple Triage and Rapid Treatment* (mSTaRT) triage algorithm, as it is shown in the work of Paul et al. (Paul et al., 2009), can be automated. We believe that all necessary vital data recordings and the embedded guidance for first responders should be integrated in a small, cost-efficient and easy to attach sensor system. Hence, our proposed solution is an *Intelligent Triage* (ITRI) bracelet to be worn at the wrist. The continuous non-invasive acquisition of relevant vital data in this scenario is difficult. This work focuses on the integration of wrist worn blood pressure measurement. The acquired continuous vital data might not only be used to semi-automate the triage decision, but it might

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be used to forecast deteriorating patient conditions.

2 CURRENT PREHOSPITAL TRIAGE SYSTEMS

The procedure for a prehospital triage in the case of a mass-casualty incident (MCI) is defined by national regulations or laws. In this work we will focus on the mSTaRT triage algorithm, as it is shown in the work of Paul et al. (Paul et al., 2009), because the Bavarian directive about MCIs incorporates a "Bavarian Model" of the mSTaRT algorithm (Schmöller and Hagen, 2017).

The prehospital triage in the event of MCI is organised as follows: The first arriving paramedic automatically becomes the operational leader. To estimate the number and severity of casualties every available first responder with dedicated triage training starts in a team of two with a first comprehensive triage. Patients with a chance of survival are grouped in 3 categories: SK 1 (red) - life threatening - immediate care/transport, SK 2 (yellow) - seriously injured - transport based on urgency, SK 3 (green) - slightly injured - transport when available. Every patient that is able to walk is categorised in SK3 (green). If a life ending injury is present a physician needs to confirm the death. Every patient that is not able to walk is assumed to be SK 2 (yellow). If one condition from a checklist of immediate life threatening conditions is met the patient is classified as SK 1 (red). This checklist includes checks for spontaneous breathing, a reasonable breathing rate, spurting bleeding, radial pulse and a check whether the patient can execute simple commands. Patients are marked with paper triage cards and barrier tape according to their triage level. Classically the situation overview has to be aggregated manually (Schmöller and Hagen, 2017; Paul et al., 2009).

Ideas for how to improve the prehospital triage with technical aid were already published. In the following the use of vital sensors and the triage automation incorporated in these systems is recapitulated.

The commercially available system *RescueWave* is an electronic replacement for the triage card that is coupled with an application that tracks and visualizes severity and position of each patient and also supports transport organization. No vital data is recorded (RescueWave, 2022).

In the literature multiple advanced electronic triage tags that enable victim tracking, continuous vital data monitoring and medical data exchange over information networks have been presented. The *Wireless Internet Information System for Medical Response in Disasters* (WIISARD) limits the use of vital data to a pulse oximeter (Lenert et al., 2011). The *CodeBlue* project focused on the sensor network for emergency responses and demonstrates vital data aggregation with an exemplary pulse oximeter and a two-lead electrocardiogram (ECG). The authors expect that more vital data sensors will be available in the future (Lorincz et al., 2004). For the *Advanced Health and Disaster Aid Network* (AID-N) an electronic triage tag that integrates a pulse oximeter, blood pressure arm cuffs and a two-lead ECG was developed. Vital data is continuously monitored and an alarm is raised on patient specific thresholds (Gao et al., 2007). The authors of the AID-N network point out that an arm cuff to measure non-invasive blood pressure has to be attached properly to deliver accurate sensor reading which might be challenging with clothed patients. Furthermore, the cuff adds extra material cost and makes the system much larger (Gao et al., 2006).

Automation of the triage decision based on electronic triage tags has also been studied in the literature. The *eTriage tag* comes in a version that measures blood oxygen saturation (SpO2) and heart rate with a pulse oximeter and an extended version that additionally measures the breath rate via a nasal cannula. The triage category can either be manually set by the triage officer or in a simple triage mode the priority is deduced from heart rate and SpO2 threshold values (Sakanushi et al., 2013). A Korean electronic triage system measures the heart rate, the SpO2 and the respiratory rate with a pulse oximeter. Additional information including the body temperature, the blood pressure, the consciousness of the patient and the walking ability can be set by a first responder via a mobile app. The triage category is automatically determined based on a checklist of combined patient conditions (Park, 2021). One German triage tag introduced the concept of pre triage levels as a general and simple reference. To determine these pre triage levels accelerometer-based activity classification differentiates walking patients, i.e. minor affected, and lying or sitting patients, i.e. major effected. Additionally, a pulse oximeter records the SpO2 as well as the heart rate and thresholds for triage levels are defined. During real emergencies it was found that especially minor affected patients tend to temporally stop moving without clinical relevant reasons, which hindered the detection of minor affected patients based on activity classification. The vital data based triage classification was better at identifying the minor affected patients but struggled to clearly identify the major affected ones (Rodriguez et al., 2014).

3 PROPOSED PREHOSPITAL TRIAGE SYSTEM

We envision an intelligent triage system that utilizes the available man power at a mass-casualty incident by enabling first responders without explicit triage training to perform the prehospital triage. Therefore, we introduce the concept of an easily attachable *Intelligent Triage* (ITRI) bracelet that records vital, position as well as movement data and features embedded triage guidance. With this system patients could be monitored continuously to detect condition changes. Additionally, machine learning methods could forecast triage category changes. The location of all patients could be shown on a central device with an overview map to give the operations manager a clear situation picture. Figure 1 displays a schematic representation of this system. It would allow the first responders to monitor the whole mass-casualty event well-arranged and continuously over the total first aid intervention period.

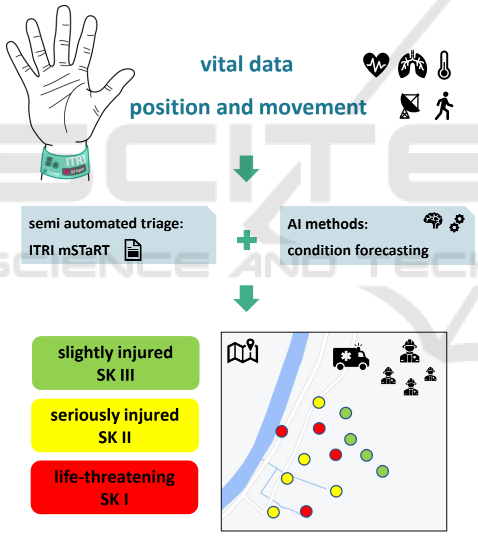

Figure 1: ITRI-system vision: The ITRI bracelet records vital data as well as position and movement data. Based on this data the triage levels are determined with a semi-automated algorithm, which is based on mSTaRT. AI methods are used to forecast condition changes. On a central device the health state of all patients during a mass-casualty incident can be monitored.

3.1 Prehospital Triage Algorithm

As argued before, the semi-automated prehospital triage algorithm of the ITRI bracelet will be based on the mSTaRT algorithm (Paul et al., 2009). We identified the parts of the mSTaRT scheme which might be automated with vital sensor or position and movement data and show the resulting triage classification scheme in Figure 2. After attaching the ITRI bracelet, the first triage decision depends on the patient's ability to walk to a collection point. This can be supervised by GPS in combination with accelerometer-based movement detection. At the collection point a critical finding checklist is assessed. Besides checks that have to be conducted by a medical expert, the list also includes threshold values for the respiratory rate, the SpO2 and the systolic blood pressure. Patients that are not able to walk are tested for spontaneous breathing. The check for spontaneous breathing as well as the respiratory rate can be deduced from a pulse oximeter. If no spontaneous breathing is detected, the first responder should clear the airways. When the life-saving measure is not successful a medical expert has to be called to the site to determine the chances of survival with the help of an electrocardiogram. Next, the respiratory rate is checked. Detection of squirting bleeding is not recognizable with vital sensor data. Thus, the ITRI system needs a user interface, which asks the first responder to check for squirting bleeding and an option to send for a medical expert if necessary. Next the presence of radial pulse is assessed. Lastly the system needs to interact with the first responder to test the consciousness of the patient, for example with a simple movement instruction.

The necessary user interface between the first responder and the ITRI system, which might be a combination of speech commands and buttons for user feedback, is outside the scope of this work. As discussed in section 2 the necessary hard- and software for victim tracking has been addressed in the literature. Furthermore, the feasibility to use a pulse oximeter to obtain SpO2, the heart rate as well as the respiratory rate have been shown. A two-lead electrocardiogram has also been integrated in electronic triage tags already. In the classic mSTaRT the use of an electrocardiogram is limited to the determination of death. ECG readings might be helpful for continuous patient monitoring, but the attachment of an ECG also takes a relatively long time. The systolic blood pressure is a vital parameter used in the critical finding check list, but an automated measurement with an arm cuff has practical limitations. Therefore, this work focuses on a concept for a wrist worn non-invasive intermittent blood pressure measurement. Additionally, such a system would also be able to detect and quantify the radial pulse.

3.1.1 Potential Triage Forecasting

As outlined on the right side of Figure 2 the continuous recording of vital sensor data in combination

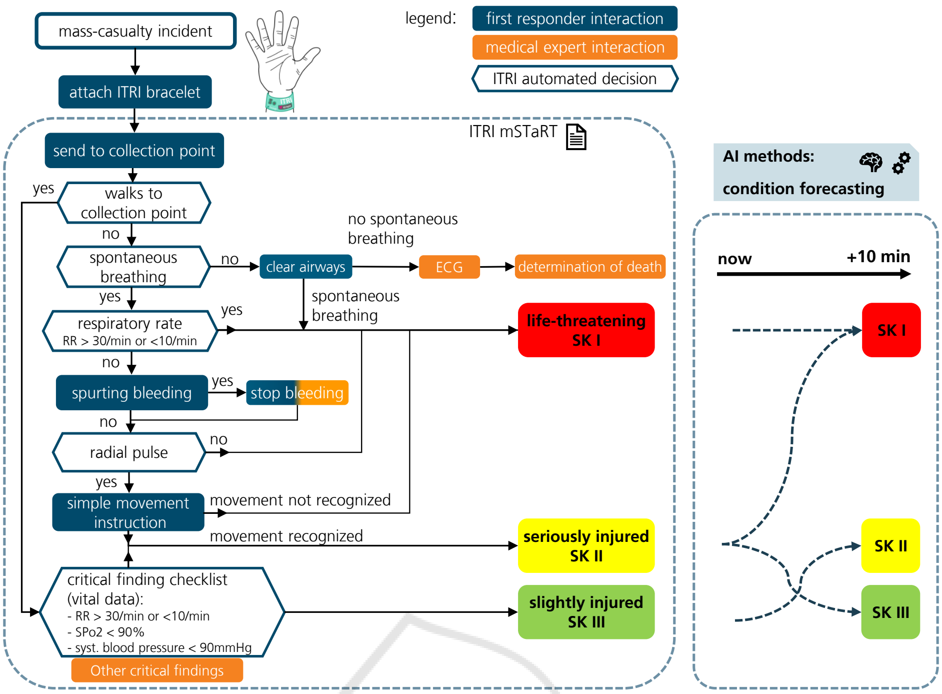

Figure 2: Proposed semi-automated prehospital triage scheme which is based on data from the ITRI-bracelet and is supposed to be performed by non professional first responders.

with available static patient data could be used to forecast the triage status with machine learning methods. This can improve the continuous monitoring of patients, because the medical experts can focus on patients with worsening conditions. A challenge for the development of machine learning algorithms is the scarcity of available data: Data from mass-casualty incidents is difficult to obtain, because these incidents happen relatively rare and complete documentation is not guaranteed. Additionally, no continuous monitoring of vital signs is currently used.

In the literature, studies with static data from a pre-hospital setting or clinical daily routine suggest that the triage could be improved with machine learning models. One retrospective study with data from two emergency departments took vital signs, the chief medical complaint and active medical history to predict likelihood of acute outcomes. Compared with the emergency severity index the proposed random forest model showed superior results. (Levin et al., 2018) Another study analysed data in two regions in the Netherlands to improve pre-hospital triage. The study identified eight significant predictors based on clinical reasoning and built a regression model to predict whether a patient is severely injured and thus needs to be transported to a higher level trauma center. The authors also present a mobile app that advises to which trauma center a patient should be transported (van Rein et al., 2019).

When continuous vital data is available, machine learning methods for times series data are applicable. The PhysioNet/Computing in Cardiology Challenge 2012 challenged participants to predict the in-hospital mortality of intensive care unit patients based on five general static descriptors and 36 time series of vital signs and laboratory results. Multiple methods of competitors have shown to obtain significantly better scores compared to a classic acuity score baseline algorithm. Beside the conventional logistic regression other model architectures like support vector machines, neural networks, random forests and ensemble learning methods were used by participants (Silva et al., 2012). This challenge was based on the MIMIC data set. This data set is recorded at critical care units of the Beth Israel Deaconess Medical Center and the newest version is organised in modules that reflect the provenance of the data. For potential triage forecasting algorithms the emergency department and intensive care unit modules are the most relevant (MIMIC, ; Johnson et al., 2022).

To potentially integrate machine learning models trained on clinical data into the ITRI bracelet one has to use transfer learning techniques. For this use case differences in vital data sensors and sample rates as well as inhomogeneous patient populations propose challenges. Lastly, a validation with real mass-casualty incident data is indispensable.

3.2 Blood Pressure Measurement

The blood pressure (BP) readings have to be non-invasive and enable automated intermittent monitoring during the whole duration of an emergency response. The selected approach is the oscillometric measurement method. This method is in widespread clinical and ambulatory use for automated cuff based BP measurement systems, that either measure at the arm or at the wrist.

3.2.1 Oscillometric Measurement Principle

The automated oscillometric BP measurement with electronic readout via a pressure sensor is based on the work of Ramsey (Ramsey, 1979). The typical measurement principle is well described by Sharman et al. (Sharman et al., 2022) and consists of the following steps: A pneumatic cuff with an integrated pressure sensor is placed around the arm and inflated to a pressure greater than the systolic blood pressure. Then the cuff is deflated and the pressure sensor records the pressure decrease overlayed with a pulsatile component, i.e. the pulse waves. These pulse waves result from the pulsatile heartbeat and can be analysed separately after high pass filtering. During the cuff pressure decrease the pulse wave amplitudes first increase sharply when the cuff pressure is near the systolic BP, then the amplitudes reach a maximum when the cuff pressure is equivalent to the mean arterial BP and for even lower cuff pressure the amplitude of the pressure waves decrease again. The recorded pulse waves during the cuff pressure decrease is called the oscillometric waveform and the approximation of their amplitude change is called the oscillometric envelope. The cuff pressure at which the oscillometric envelop is maximal is equivalent to the mean arterial BP. The systolic BP is typically estimated to be the cuff pressure at the rising site of the oscillometric envelope at about 50% (range 45–73%) of the maximal amplitude. Equivalently the diastolic BP is typically estimated to be the cuff pressure at the falling site of the oscillometric envelope at about 70% (range 69–83%) of the maximal amplitude (Sharman et al., 2022).

The oscillometric measurement method has some known drawbacks. The placement of the device relative to the heart can alter the BP measurement due to hydrostatic pressure effects. During the measurement the patients should not move. Conventional oscillometric BP measurements are known to underestimate systolic BP (Sharman et al., 2022). Differences of arterial stiffness, which for example can be observed in elderly or diabetic patients, also influence the accuracy of the measurements (van Montfrans, 2001). It remains to be evaluated if these drawbacks prevent the usage of the oscillometric method.

3.2.2 System Implementation

The BP measurement component should be a small and lightweight system that is comfortable to wear and easy to use.

Generating a varying cuff pressure with a precise resolution on a small footprint is a challenging task that can be solved with micropumps. We propose the use of piezoelectric micropumps to combine high pressure generation (25 kPa), large enough flow rates (50 ml/ min), a relative low power consumption (<300 mW) as well as a small system size (Ø 20 mm x 2.1 mm) (Bußmann et al., 2021b; EMFT Steel Pumps,). The operating principle is based on the indirect piezoelectric effect that describes the mechanical deformation of a material due to an applied electric field. The actuator is a piezoceramic, because this material exhibits a strong piezoelectric effect. An alternating voltage at the piezoceramic actuator leads to its extraction and contraction, which bends the metal diaphragm it is glued on. The bending displaces the volume inside the pump chamber and moves the fluid according to the two integrated passive check valves (Bußmann et al., 2021a). Figure 3 presents the schematic layer-stack of a metal micropump that can be used to generate the cuff pressure.

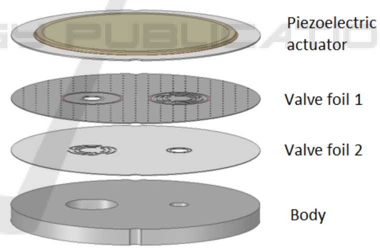

Figure 3: Diaphragm micropump consisting of four layers: Body plate with holes, two valve sheets in the middle, and an actuator with a piezoelectric element on top.

In Figure 4 a schematic representation of the complete fluidic setup is shown. The piezoelectric micropump fills the cuff with environmental air to generate the required cuff pressure. An integrated pressure sensor is used to measure the cuff pressure and the pulse waves. A flow restriction with a high fluidic resistance in parallel to the micropump acts as a over-pressure protection and pressure relief. Since the cuff pressure is directly controlled by the actuation frequency of the micropump the pressure build up can be precisely controlled. This enables to measure the oscillometric waveform during the pressure build up.

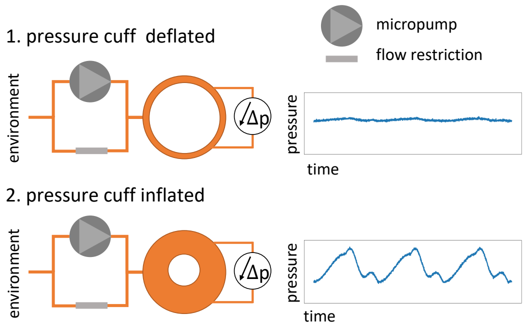

Figure 4: Fluidic principle of proposed oscillometric blood pressure measurement method (figure taken from (Gruenerbel, 2022)).

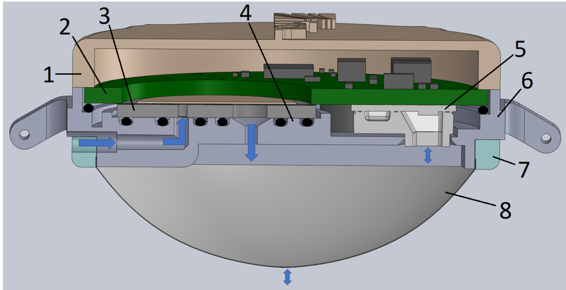

Figure 5: Cross section of the blood pressure monitoring bracelet with: 1) housing lid, 2) PCB with electronics, pressure sensor and contact pad for micropump, 3) the metal micropump, 4) rubber sealings, 5) a pressure sensor, 6) the outer housing with integrated fluid channels, 7) a fixture for the elastic foil, 8) the elastic foil, i.e. the pressurised area.

Our design does not use a complete cuff, but a pressurised area that is fixated to the wrist by a bracelet. During system design a proper placement of the pressurised area with its center above an artery is ensured as suggested for the centre of an arm cuff by Petrie et al. (Petrie et al., 1986). Furthermore, we apply a pressurised area that is large enough to ensure good signal quality but still comes with a reasonable filling time. Figure 5 shows the current state of the housing and the integrated electronics of the BP measurement bracelet. The Housing consists of three 3D-printed parts, which are manufactured using stereo lithography. The 100 µm thick thermoplastic polyurethane foil at the bottom of the housing is pressed against the housing base with a ring. Additionally the foil is glued to the housing base. The ring fixating the elastic foil and the upper housing lid are pulled together with four screws. The rubber seals between the micropump and the housing base are compressed when the upper housing lid presses down on the printed circuit board, pushing the micropump in the housing base. To make silicon sealing easier, a chamber is positioned at the pressure sensor opening. The fluidic channels are printed directly into the housing base. The air inlet is positioned opposite the wrist strap mounting arms so that it will be hidden behind the wrist strap to prevent unintentional blocking of the inlet. A rubber wrist strap that is commercially available is used.

3.2.3 Feasibility Study - Results

The introduced BP monitoring system is tested in an early feasibility study. Therefore, a test person wears the bracelet. As soon as the applied pressure is high enough, the pulse waves become visible. An exemplary pulse wave recording is shown in Figure 6. The y-axis represent the measured pressure inside the pressurised area. The pressure pulses can be distinguished clearly. It should be feasible to calculate the mean arterial blood pressure and estimate the systolic and diastolic blood pressure using the algorithm for the oscillometric method described in section 3.2. Additionally, the sensor readings can be used to quantify the radial pulse and the heart rate.

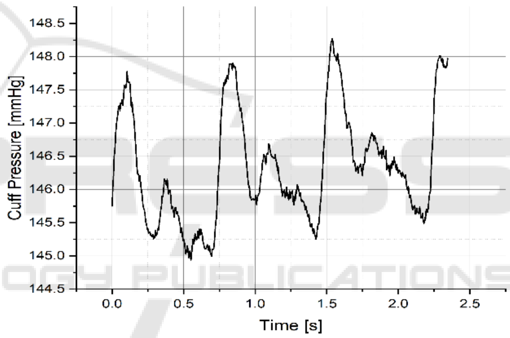

Figure 6: Exemplary measurement of blood pressure pulses acquired with the presented demonstrator.

4 CONCLUSION

It was analysed which part of the mSTaRT algorithm can be automated to potentially enable all first responders to perform a semi-automated prehospital triage. As a step towards integrating all necessary vital data sensors a small, cost-efficient and easy to attach prototype of an oscillometric blood pressure monitoring bracelet was designed and build. Measurements with the demonstrator show promising raw sensor value readings with clearly identifiable pressure pulses. The exact algorithm to determine the oscillometric envelope and the calculation of the systolic and diastolic blood pressure values remains to be defined. The blood pressure reading must than be verified with, either an intra-arterial measurement or the classic auscultatory method with a sphygmomanometer.

The integration of all other vital data sensors, the position determination, the movement detection, the embedded triage guidance together with the user interface of the bracelet as well as the central situation overview still have to be designed.

The integration of machine learning to forecast possible triage status changes is an interesting research topic. In both prehospital and clinical settings data based triage models show promising results. A prehospital triage forecasting model based on time series data can only be developed after it was determined which vital data can be measured continuously during a prehospital triage.

The effectiveness of an electronic triage system can only be validated with emergency drills or even better with real emergency situations. Especially our assumption that first responders without specific triage training are enabled to perform a semi-automated prehospital triage has to be verified this way. Additionally, in the same manner, the validity of the proposed blood pressure measurement method must be confirmed.

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