Using NLG to Manage Information in Medical Emergencies

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ABSTRACT
When a medical emergency occurs in a rural area of the UK, the first person on scene (FPOS) may be a layperson with some basic first aid training and limited equipment. That person must assess the patients and their situation, carry out basic treatments and seek additional help as appropriate. This paper describes the potential use of Natural Language Generation (NLG) to generate advice to the FPOS at a road traffic collision and more effective handover reports between the FPOS and the subsequent medical staff in the patients' chain of care.

1. INTRODUCTION
Having local General Practitioners (GPs) on call around the clock is no longer sustainable in rural communities. Future health policy expects a mixed economy, in which citizens will work alongside health professionals of varying levels of training, adopting a team approach to deliver care to patients with acute and/or chronic medical problems.

In this scenario, the FPOS at a road traffic collision (RTC) in a rural location may have limited medical expertise and yet may be the only source of help until an ambulance arrives, possibly hours later. Somehow they have to assess the medical condition of patients, take the most important actions to ensure their survival, and inform the subsequent medical staff in the patients' chain of care of the patient's status. Such information has been demonstrated to lead to better decisions [1].

The training of members of the public to act as FPOS is currently undertaken on a limited scale by organisations such as the Scottish Ambulance Service. Such trained "Community First Responders" record some of the patient's physiological parameters every five to ten minutes and write them down as convenient. They are also meant to fill in a Patient Report Form (PRF), which is to be handed over to the receiving ambulance crew at the scene of the incident, and to the ambulance service within 24 hours of the incident. However, this does not occur routinely. The FPOS do not have enough time to complete the paperwork when they are with the patients. They tend to give a verbal handover to ambulance crews and fill in the PRF later.

When ambulance crews take over, they also carry out their own assessment, and fill in their own PRF, which may be sent electronically to A&E units if the necessary communications are in place and are enabled. Upon arrival at hospital, ambulance crews will give receiving medical staff a verbal handover, and handover the FPOS's PRF, if they received it.

The current process clearly hampers the confidentiality, integrity, and continuality of the patient's data as it is transferred among the responsible parties. The MIME (Managing Information in Medical Emergencies) project aims to tackle this problem by integrating portable physiological sensors with a mobile device that will allow the FPOS to record and manage multiple patients' physiological data as well as observations and actions taken by the FPOS. The information gathered would be used to recommend appropriate actions to the FPOS if needed, and presented to the subsequent medical staff involved with the treatment of the patients to support their decision making process.

The value of such information in supporting decision-making is only realised if it can be communicated effectively. Recent research has shown that compared to the common graphical visualisation, textual summaries of large volumes of complex medical data composed by human experts can lead to better decision-making by medical staff with a time constraint of a few minutes. This was especially true for the staff with less experience [2]. Therefore, textual summaries could be the most effective mode of data presentation for MIME. However, human generated texts are unfeasible to implement. We propose that NLG can be used to automate the generation of such summaries.

Being able to recommend appropriate actions to the FPOS could be highly valuable given the rate of skill decay in medical staff in rural areas (as fast as four weeks in staff with less expertise), and the infrequent encounters with medical emergencies (e.g. 2% of rural GPs' yearly workload). However, while electronic clinical Decision Support Systems are valued in principle, usage in practice may be low [3]. One possible reason for this is related to the users' perception of such a system. The system's advice is often ignored, particularly when it is not accompanied by feedback showing the benefits of using a decision rule [4], or longer and strongly confident explanations [5]. In MIME we aim to sidestep this problem by generating texts that primarily inform and only to a limited extent recommend actions.

2. RELATED WORK
Generation of textual summaries or recommendations from complex medical data is not a novel idea. The most accomplished and well evaluated system known to us was BT-Nurse, a system that can generate textual summaries from neonatal intensive care data [6,7]. An evaluation study showed that there was room for improvement. The computer generated summaries were as effective as the graphical visualisation of the data, but they were not as effective as the human generated counterparts [2].

3. RESEARCH CHALLENGES
Firstly, given the vast amount of data collected and the little time that medical staff have to process it, only the most relevant information should be presented in the most comprehensible order. What information do different medical staff (e.g. FPOS, paramedics, A&E doctors) require? What impact does the information have on their autonomy, and confidence in taking actions? How should the system choose between explaining a

situation, describing the patient's medical status, or justifying and suggesting an action? For instance, Figure 1 shows a number of different alerts that describe the same event.

A strongly confident alert with explicit recommendation: The casualty has a serious breathing problem! Check the airway for obstructions again, and if there aren't any then insert an airway adjunct!

A strongly confident alert with implicit recommendation: The casualty has a serious breathing problem! Have you considered inserting an airway adjunct?

A weakly confident alert: There is a possible breathing problem here!

Figure 1: Examples of different alerts.

Secondly, despite the benefits of human generated textual summaries of complex data over graphical presentation in supporting decision-making, computer generated texts have not enjoyed the same level of success. Human generated texts have been suggested to have better narrative flow and richer textual details. Not only is a single event better described but also descriptions of multiple events are better grouped together to make a meaningful story. Could enhancing the naturalness of the computer generated texts improve their effectiveness?

Thirdly, our initial reviews with various medical staff (see Section 4) indicated that the handover reports must include certain information that would most likely to be obtained in the form of free-text. Integrating such type of data in the generated texts while maintaining their coherence proves to be a challenge. Figure 2 shows an example of a possible handover report.

4. WORK SO FAR

Development of RTC scenarios: A number of realistic RTC scenarios are required to build decision rules and to evaluate the system. Working with various medical experts, we have been collecting real life scenarios or developing realistic scenarios. Each scenario must describe in detail the condition of the patient, the actions taken, and the reasons for taking the actions. Where real life data cannot be obtained, a scenario is programmed into simulation software that can generate realistic physiological signals.

Gathering information requirements of handover reports: Interviews with different medical experts of both urban and rural areas have been carried out to identify their information needs. Preliminary results indicated that beside physiological data and data trends that can be captured by sensors, some crucial information would require manual input from the FPOS in the form of free-text. Such information includes the detailed mechanism of injuries (e.g. the patient was hit by a car, the speed and the direction of the collision), the appearance of the patient (e.g. signs of bleeding, pale skin, level of consciousness).

5. CONCLUSIONS

This paper introduces MIME, a new project designed to support the FPOS of medical emergencies such as RTCs. The project has three goals: (1) capturing an accurate flow of the patients' physiological data, together with diagnoses and actions taken by the FPOS, (2) to a limited extent, recommending appropriate actions to the FPOS, and (3) generating handover reports as the patients are passed from the FPOS to paramedics and subsequently A&E doctors. We propose to use NLG to generate the handover reports and real-time recommendations of actions. We aim to extend previous work (e.g. [6,7]) to incorporate more extensive use of free-text data entries, and to investigate whether tailoring and improving the naturalness of the texts generated can increase their effectiveness in support decision-making.

PATIENT AND CURRENT STATUS: 40 year old male patient. He is responding to pain, but not voice. His airway is clear and he is breathing at a rate of 14 breaths per minute. There are no obvious signs of bleeding. He is currently being given 100% O_2 and his blood oxygen saturation is 95%. His pulse rate is 90 bpm.

MECHANISM OF INJURIES: He was hit on his right side by a car. The car was travelling at about 30 mph. He rolled up onto the windscreen and landed on his left side. He has not been moved since.

INITIAL ASSESSMENT: He was unconscious and did not respond to voice or pain. His neck was flexed and his breathing was noisy and difficult. He was breathing at 18 breaths per minute and his radial pulse was 120 bpm. His capillary refill was normal but his face was pale. There were no obvious signs of bleeding.

ACTIONS AND FINDINGS: A jaw thrust manoeuvre with C-spine protection was performed at 10:30. His rate of breathing dropped to 14 breaths per minute and his pulse rate dropped to 100 bpm. High flow oxygen was then applied at 10:31. Breathing rate was maintained at 14 breaths per minute, pulse rate dropped to 90 bpm and blood oxygen saturation was 95% on 100% oxygen (92% on air). He then responded to pain.

TREATMENT: Oxygen therapy given at 10:31 (100 % O_2).

Figure 2: An example of a handover report.

6. REFERENCES

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