Design Considerations for UAV-Delivered Opioid Overdose Interventions

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***Abstract*— With recent regulatory changes that allow for commercial unmanned aerial vehicle (UAV) operations, there has been increasing interest in using UAVs, aka drones, for delivery of medical care, especially in rural areas. Previous work has focused on Automated External Defibrillators (AEDs) for people in possible cardiac arrest, but there are potentially many other emergency medical interventions that could be made more readily available through drones. One such use includes treatment for opioid overdoses, which could be significant given the current US opioid crisis. While drone delivery of blood has been established in Africa between medical professionals, there are no established applications of drones delivering emergency medical interventions for use by bystanders due to technical issues in the safe operation of drones in the air and in accessing and using the medical devices on the ground by laypersons.**

This paper examines how such a drone *system* should be designed in order to promote safe and effective operations for all stakeholders. This complex system design problem should be addressed at both local and global levels. At the local level, new theories and applications of human-technology interaction should be developed considering the need to promote safe and efficient human interaction between bystanders and drones delivering emergency medical interventions. Resulting models will need to consider how affordances can be designed into the technology given the use by untrained bystanders. Given that these emergency drones will need to be remotely supervised, the global aspect of this research should focus on the development of a drone supervision/dispatch capability, which will include interacting with the layperson who initiated the emergency call and determining how to integrate new network optimizations models so that dispatchers can understand when and where to dispatch drones and/or ambulances.

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1. INTRODUCTION

With the recent explosion in the availability of small unmanned aerial vehicles, aka drones, including regulatory changes that allow for commercial drone operations, there has been increasing interest in using drones for medical applications. In 2015, NASA teamed with Flirtey, a small drone company, to deliver medical supplies in Southwest Virginia [1]. In 2016, Flirtey also demonstrated their ability to deliver insulin and first aid kits to medical professionals [2]. More recently, a group in Switzerland demonstrated the ability of hospitals to exchange laboratory samples via drones [3]

Previous examples showed, through one or a handful of flights, that delivery of medical cargo by drone is *possible*. Despite these demonstrations, there has been no established use of drones for delivery in the US, medical or otherwise. The only established drone medical delivery service in the world today is happening in Rwanda, where Zipline has performed about 1,400 deliveries of blood [4] and projected it will start similar operations in Tanzania in 2018. In these deliveries, parachutes or tethers were used for the actual deliveries to a trained receiving team on the ground below.

A few researchers have proposed extending this idea of medical supply delivery to transport of Automated External Defibrillators (AEDs) for people in suspected cardiac arrest [5, 6]. The basic idea is that a person witnessing a subject experiencing a sudden loss of consciousness, possibly

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indicating cardiac arrest, can call 911 who simultaneously initiates EMS and drone/AED launch. Cardiac arrest is the most time sensitive emergency in medicine since brain cell death starts to occur after about 3 minutes of cessation of heart activity, so getting the heart restarted with a defibrillation shock as quickly as possible is essential. Current EMS/first responder performance, however, has achieved no better than about 10% survival at 30 days without neurologic impairment, making cardiac arrest one of the deadliest conditions in all of medicine. These statistics have not improved despite 30 years of work.

Experience with AEDs in controlled spaces, particularly airplanes and casinos, has shown that survival can be increased to 40-70% if AEDs are used. Since a drone could reach a victim faster than an ambulance or first responders (police, fire) in some locations where witnessed cardiac arrest occurs, a strategically-located drone-AED system offers the possibility of a breakthrough in our ability to save lives following sudden cardiac arrest. The societal/public health impact thus has the potential to be huge, eventually saving tens of thousands of lives each year at the national level.

Moreover, to be cost effective for individual communities to add this capability to their current EMS system, scalability and the degree of care enhancement provided by the drones needs to be explored. For example, a network of drones that could deliver AEDs could also deliver additional emergency medical interventions in similar time critical situations such as naloxone nasal spray, which is a narcotic antidote used when opioid overdose results in respiratory distress. Opioid overdosing, from heroin or prescription medications is a national epidemic and the main driver of drug overdose deaths [7]. Recent research has shown that laypersons with naloxone kits who witness an opioid overdose can help reduce opioid overdose mortality [8]. Making naloxone nasal spray and other similar emergency treatments available in such a timely and directed manner could significantly improve opioid overdose outcomes.

There is a clear need for improved and timely emergency care, especially in rural areas or highly congested urban settings, where drone delivery of emergency medical interventions like AEDs and naloxone nasal spray could make a tangible difference. However, to date there have been no studies on how such systems should be designed to consider the interactions with laypersons in these settings, or how 911 dispatchers would or should make decisions to send a drone in addition to an ambulance. This paper looks at a framework on how such a drone *system* should be designed in order to promote safe and effective operations for all stakeholders, including a predictive model on where and when an opioid overdose could occur, to further elucidate the effect of a drone system on a single medical complaint.

Understanding that drones could play an important role in emergency medical interventions, it is imperative that we move beyond conducting eye-catching demonstrations to a principled and comprehensive research program to fully understand the options for and implications of developing and deploying such safety-critical systems. To this end, several important questions arise including:

1. How should the drone delivery system interact with the laypersons or bystanders who would become the medical providers on scene? Bystanders may feel responsible for providing time-sensitive life-saving care, which could cause undue stress. The delivery of the medical supplies through the approach and landing sequence with rapidly rotating blades on the drone could cause a high stress situation with potential for injury, and not all bystanders will be comfortable in such environments.

2. How would a predictive model of opioid overdose locations and frequencies inform selection and stocking of drone stations? One assumption has been that drone stations would be based in the same locations as the ambulances themselves, or evenly distributed within a geographic area. However, predictive modeling of incidences of overdose could challenge that assumption by considering seasonal to diurnal variation of opioid users' movements. Since moving a drone site may be easier than an ambulance garage, this could improve the efficacy of drone usage without requiring as large an increase in number of drones themselves.

3. How should 911 dispatchers be supported who must make the decision between initially sending a drone and an ambulance or just an ambulance? Such dispatchers will need decision support software that helps them understand if and when to send a drone in an emergency, and how and when to follow up such responses with ambulance dispatch. Moreover, in many settings like during a natural disaster, there will be times when there are more emergency scenarios than either available drones or ambulances. So, how to prioritize the assignment of drones and ambulances to first response calls should be a critical future consideration.

2. Previous Drone Emergency Medical Intervention Research

A recent study examined EMS response times in urban, suburban, and rural areas using data from nearly 1.8 million patient encounters [9]. This study highlighted that while average response times from a 911 call to responder on-scene arrival was 7 minutes, the median time more than doubled to 14 minutes in rural settings. In these regions, which accounted for 4% of the overall volume of calls, 10% of people waited approximately 30 minutes. Another study showed that traffic congestion in urban and highway settings, on average, added approximately 10 minutes to emergency response times [10]. Delayed EMS response times have been associated with worse patient outcomes in trauma, cardiopulmonary arrest, severe bleeding, and airway occlusion patients, with higher mortality rates in rural settings [11] [12, 13].

Out-of-hospital cardiac arrest (OHCA), aka sudden cardiac arrest that occurs in the community, is one of the most time sensitive emergencies requiring fast response times. OHCA affects over 350,000 victims annually in the United States, with an average overall survival rate of 8.3-10.6% [14, 15]. Survival is highest in OHCA patients who are given electrical defibrillation (a “shock” delivered by an AED device) following the cessation of heart activity, and the best survival occurs when defibrillation is provided within 3-5 minutes [16]. Every minute that elapses after arrest without defibrillation is associated with a 10% decrease in absolute survival rates [17]. Even with a relatively rapid response time of 8 minutes, a typical goal for EMS services across the country, survival remains extremely poor.

Previously, only a single group has conducted scientific research in OHCA with drone delivery, using repeated trials to determine how actual drone AED flight distances and response times compared with ambulance response times [6]. Using data from EMS response times of prior OHCAs, 18 flights were conducted over distances that ranged from 15-8927m, with total time from dispatch to drone arrival ranging from 1-12 minutes. Drones were reported to be statistically faster overall than ambulance response times. While this study provides an important proof of concept, it did not address the larger system issues, including the impact on 911 dispatch, how interactions with bystanders could be supported and it only looked at a single medical indication when drones could be used.

Neither the Claesson et al. (2017) or Boutilier et al. (2017) study addressed either the time it takes to determine whether to send a drone or an ambulance alone, nor did they consider the time it takes for a bystander to safely approach a drone, remove the medical equipment, and then apply it in an appropriate manner. Future efforts should extend this research by addressing the added time at the beginning of the dispatch process, as well as in the therapeutic stage where bystanders access and properly use the medical devices brought by the drones and increase the medical indications which drones should be considered for. No published research to date has investigated how actual bystanders would interact with such technology that is inherently very dangerous (primarily due to the spinning blades). Moreover, none have addressed how the initial decision would be made to send an ambulance alone versus sending a drone first, with a following ambulance. Indeed, the problem is really one of staggered dispatch, which requires new forms of optimization and planning.

3. Opioid Overdose

Opioid overdose, which can lead to complete cessation of breathing, is another example of an extremely time sensitive condition that if not treated within minutes, can lead to severe neurological damage and death. The opioid overdose crisis has been declared a public health emergency and is currently the leading cause of death for Americans under 50 years of age. Over 33,000 people died as a result of opioid overdose in 2015, a number that has doubled in just 8 years [18]. The generic drug naloxone is an opioid receptor blocker that can completely prevent brain damage and death if given promptly (within minutes) following cessation of breathing by overdose victims. Increasing access to naloxone for opioid overdose rescue is one of the US Department of Health and Human Services’ three priority areas for responding to the opioid crisis [19].

The nasal preparation of naloxone comes in a single, pre-filled, pre-measured dose that is fast acting, easy for a bystander to administer with very few risks and no adverse effect in people who have not taken opioid drugs. Thus, suspicion of the cause is enough justification for treatment without the need for complex diagnosis. Despite the urgency of the problem and the ease, safety, and success of treatment, only 8% of US counties had established overdose education and naloxone distribution programs in 2014, and only 13% of counties with the highest overdose mortality rates had such a program (Lambdin, 2017) even though bystander administration of intranasal naloxone spray is associated with significantly increased odds of recovery compared with no application [20, 21].

4. Challenges in Supporting Laypersons

Most existing literature on untrained bystanders providing medical care in acute illness is in relation to CPR and AED use. Public location AEDs are available and only require a bystander perform four simple steps: turn the device on, apply the electrode pads to appropriate locations on a patient’s bare chest, and press a button to deliver a shock if the AED device advises “shock needed”. A study of mock cardiac arrest found that untrained sixth-grade children were only modestly slower at applying AED treatment than trained professionals [22].

Studies have shown that bystander use of AEDs in locations where static (fixed location) AEDs are available remains very low [23]. In the U.S., only 4.5% of bystanders use an AED before EMS arrival on the scene [24]. Preliminary studies have indicated that although bystanders with prior CPR training are reassured by the simplicity of an AED device and find it contributes to resuscitation attempts, others may feel additional distress, particularly without prior CPR and AED training [25, 26]. In one study examining bystander interaction with publicly available AEDs, providing customized emergency operator assistance reduced user errors [27], so given the complexity of retrieving medical devices from a drone, such as the naloxone spray, such assistance will likely be critical. Moreover, the number of bystanders at the scene [28], as well as their relationship to the patient [29], can all affect the final outcomes.

Bystanders administering naloxone intranasal spray to an overdose victim will first need to retrieve the medication from the drone, and it is not yet clear how the drone should be designed to ensure safe interactions with laypeople. Moreover, these bystanders may need reassurance that they will not hurt the victim and assistance with determining how and when to administer a second dose or providing additional caregiving after treatment while waiting for the arrival of EMS. Indeed, all bystanders attempting to provide emergency care through the assistance of a drone will likely need some level of coaching and thus how to bridge the gap between making a 911 call and working with a drone and a drone dispatcher is an area that needs significant research.

5. Challenges in a 911 Dispatch Support System

A key challenge moving forward with drone emergency medical deliveries will be providing 911 dispatchers additional decision support in understanding when to dispatch a drone and ambulance as opposed to just an ambulance in an emergency. This support takes the form of optimal allocation of medical resources (a limited number of available drones and ambulances) to specific emergency locations in a time critical manner. There may be multiple such locations that need services at any point of time. Each location may have just one patient and a bystander, or a patient and several bystanders, or even tens of patients and bystanders.

In many cities, the number of medical resources like ambulances and paramedics is substantially smaller than the number of patients who require immediate care. Furthermore, a drone can only provide initial assistance to a patient/bystander, as an ambulance will still need to be dispatched to each emergency location. Thus, the use of a drone cannot replace an ambulance, but rather decrease initial response time. Finally, multiple 911 dispatch centers may be concurrently involved in responding to a set of emergency scenarios depending on the geospatial spread and magnitudes of any large-scale emergencies.

Therefore, 911 dispatchers will need decision support that identifies whether a particular type of drone should serve an emergency location before an ambulance, and b) which available EMS truck/squad should serve which location(s) in what sequence. Both these decision support problems have to be solved as efficiently and robustly as possible, keeping in mind that a dispatch delay of even a minute may lead to increased likelihood of patient death, and that such operations occur in highly uncertain scenarios with limited and/or unreliable information.

While there is no published work to date on a system that optimizes both drone and ambulance allocation, there are examples of each system independently. With respect to ambulance allocation, substantial work has been reported in the context of decision support systems to aid the emergency dispatchers [30-32]. However, these works are either restricted to purely simulation-based validation of the developed systems or employ ad-hoc or post-hoc analyses to identify effective ways of designing such systems.

Significant work has looked at supporting operators in allocating unmanned aircraft/drones in resource allocation tasks, particular under time pressure which is a significant characteristic of the 911 dispatch task (e.g., [33-40]) While this work can inform the ambulance and drone dispatch problem, very little research has looked at integrating the allocation of air and ground assets to support dispatchers in a way that adds very little to their already high workload [41].

The objective of such a system should be to minimize the estimated times to serve all the emergency locations, possibly weighted based on the criticality or magnitude of the emergencies at certain locations. Here, service time includes both the time to reach a given location and the time to assist the patients in a location depending on their number, medical conditions, the availability of bystander(s), and the mode of interacting with the bystander(s). In addition, multiple sources of uncertainty in these decision support problems will need to be considered. These sources include the current locations and availabilities of the resources, supplies on the drones, traffic conditions, and the extent of the emergencies, i.e., the number and medical conditions of the patients and the number of bystanders. All of these affect the problem formulation, rendering them stochastic in nature with random decision variables, and random objective function and constraint coefficients.

New emergency services requests may come while the allocated resources are completing their services. Sometimes such requests cannot be predicted in advance, and may, therefore, require fast, dynamic reallocation of resources, suggesting the use of a decentralized framework to solve a *stochastic* optimization problem. Any resulting decision support system should also be consistent with the fact that any 911 dispatch center is only responsible for allocating a fixed number of resources within a fixed service region and needs to communicate on a per demand basis with other dispatch centers if more resources are required to address the current emergency scenarios.

Boutilier, Brooks et al. 2017 looked at the number and location of drones needed to reduce the response time for AEDs in OHCA in both high and low population densities using historical geo-coded data of OCHA locations. Aiming for a conservative estimate, they found that an appropriate drone network in a congested urban environment could reduce response time by an average of 3 minutes, and in a rural environment, 10 minutes. However, they looked at fixed locations for their drone bases, and didn't consider seasonal or other effects that might change the optimal location. Compared to cardiac events, opioid overdoses can tend to occur in clusters, both geographically and temporally depending on factors ranging from pay-period cycles to a tainted supply of an illicit source of heroin cut with a higher potency narcotic leading to a mass overdose event on a particular street corner. 911 systems currently deal with such clusters on an expert-level historical analysis basis, dynamically staging ambulances closer to known overdose areas to reduce response time, such as parking ambulances outside of large stadium sporting events. Predictive modeling of these events and clusters could allow for much more efficient resource allocation that is responsive to time-dependent variation, or other factors that develop out of the model analysis.

Lastly, one very important consideration in the development of such a system is that it should be tested with actual 911 dispatchers. This then would allow for direct comparisons with existing EMS Computer Aided Dispatch programs to determine objective workload impact as well as subjective feedback from the actual dispatchers. Designing such a decision support system with the active and continuous feedback of stakeholders is critical so that this technology can be more easily transitioned into operational settings.

6. CONCLUSION

There has been great interest in the use of drones to provide emergency medical interventions. Indeed, the previously mentioned Claesson et al. (2017) article that demonstrated drones flights could provide faster response than ambulances was the second most read article for the flagship medical journal, Journal of the American Medical Association (JAMA) in 2017 [42]. While an important initial step, for such systems to become a reality, much more work is needed beyond just demonstrations that provide a proof-of-concept. Significantly more principled research is needed at both the global dispatch and local levels of drone medical deliveries to bystanders to ensure such operations are safe, feasible, and scalable across communities ranging from small, rural with low population-to-area ratios to large densely populated urban areas.

At the local level predictive modeling of opioid overdose events or clusters can inform regional resource allocation. Designs of the drones themselves will need to take into account the actual mechanics of naloxone spray delivery to anxious and untrained bystanders, and a method to instruct them on how to deliver the medication and care for the patient until trained providers can arrive.

At the global level, 911 dispatchers are going to have to determine when to send a drone in response to an emergency call and how to follow up this initial response with an ambulance to provide follow-on care and transport to a medical facility. Such decision support requires advances in resource allocation and optimization algorithms that consider a dynamic and under-resourced environment, as well as the development of an interface that is easily understandable by 911 dispatchers that adds minimal workload.

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