A UAV for Triage Assessment of Chronic Illness in a GPS-Denied Environment

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Abstract: In this paper we conduct an extensive review of the literature toward an autonomous Unmanned Aerial Vehicle (UAV) for application in home healthcare. Based on the research findings, a system is proposed towards such a UAV for the purpose of patient care in an indoor environment, specifically in triage care for people living with chronic conditions. Our system seeks to provide an innovative solution for healthcare at home and to facilitate independent living as well as reduce over triaging through personalized robotics. The development of advanced navigation systems for UAVs has aroused extensive interest recently because of its enormous potential. In comparison to outdoor flight, GPS-denied navigation poses several distinct challenges in stability and control for quadcopter operability, including object detection and avoidance, real-time wireless client-server communications, stability and safety concerns. Medical Decision Support Systems (DSSs), which have been developed largely in the triage component of health assessment, care and decision making, also pose separate research challenges in terms of accuracy, consistency, response (processing) time and degree of automatic operation. As a single system, a drone-based DSS for chronic illness triage assessment poses unique challenges. For this application, the DSS requires voice-based responses, occurring in real-time and classified according to a dynamic and adaptive decision support engine that operates automatically; that is, with no human input and using non-invasive patient analysis. Existing healthcare systems of this nature have not yet been produced. Furthermore, patient recognition through real-time image fused with voice data in a noisy, GPS-denied environment has yet to be achieved. While path planning, navigation, control and stability concerns have been extensively addressed, accuracy for these systems can be improved and the technology as well as applied algorithms must be adapted to application-based requirements, in terms of weight, processing and dedicated communication requirements.

Keywords: Unmanned aerial vehicle, navigation, flight control, collision avoidance, assistive technologies in healthcare, speech recognition, decision support system.

1. INTRODUCTION

Whilst overall global life expectancy has increased, healthy life expectancy has not [1]. The complex care demands of aging populations, as they live longer, require innovative and effective solutions that enable self-management and for individuals to remain in their own home. Chronic diseases are the leading causes of death and disability worldwide, and pose a significant burden in terms of quality of life, loss of independence, morbidity, mortality and health care costs. In particular, Diabetes, congestive heart failure, coronary artery disease, chronic obstructive pulmonary disease and hypertension are the five chronic conditions that result in the greatest number of presentations to hospital and health care costs yet respond most favourably to effective care coordination and self-management support [2]. Self-management in the context of living with chronic conditions incorporates a set of skills but also support from health care professionals for health assessment, health prevention and early intervention in deteriorating health. Advances and developments in sensor and telecommunication technology offer solutions for achieving effective health care for this cohort [3]. We offer a technological approach to facilitate healthcare assessment in one's own home; seeking to avoid readmission to hospital and associated healthcare and emotional costs.

The proposed work focuses on the development of an effective health assessment process using a custom hardware and software solution designed specifically for the application. We propose a solution that uses an autonomous UAV to provide healthcare, indoors and within the person's home. Once recognized, the individual is questioned by the UAV that wirelessly communicates responses to a central server and retrieves further queries. Health-based queries are those that require yes/no responses and Voice Recognition (VR) strategies identify and classify the speech response. The DSS operating on the server provides patient analysis through dynamic classification to determine the best course of action for appropriate healthcare, such as alerting a primary caregiver in an emergency situation. We propose to address the following administrative challenges: reduction in undiagnosed deterioration thus reducing morbidity and hospital presentations and to reduce unnecessary hospital visitations by offering customized,

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personalized and dynamic home healthcare. We propose to address the following research challenges: designing and developing an autonomous DSS, with patient yes/no querying in addition to VR and Image Recognition (IR) strategies, by incorporating in the dynamic, intelligent, server-side classification engine existing health assessment protocols for assessing criticality of the individual's health status using non-invasive patient assessment techniques. This is to be implemented in a GPS-denied environment, in the presence of noise (caused by rotor blade motion), with no human interaction (fully autonomous), with real-time wireless communication between drone and server, and real-time processing. We examine several strategies for navigation, voice- and facial- recognition, and non-invasive DSS's, within the research literature in Section 2, with the algorithm and sensor technology most suited for adaptation to our proposed work summarized at the end of each sub-section. In Section 3 we present our proposed work, detailing the hardware component connectivity, data flow and embedded algorithms for *Healthbuddy* operability.

2. LITERATURE REVIEW

Research strategies applied for autonomous navigation, including path planning, control and stability, and obstacle avoidance, are examined with focus on methods that enable real-time, autonomous UAV flight in an indoor environment where objects may be in close proximity to the drone, may be repositioned or in motion. Methods for VR and IR are examined, toward real-time detection and recognition of a patient through speech processing and facial recognition respectively, in an indoor environment, subject to noise and movement. Instead of avoiding a patient, the drone must locate and fly within close proximity to the person, while ensuring collision avoidance. Ultrasonic and image- based strategies are considered for navigation and recognition. Once identified, the individual is questioned by the drone; non-invasive strategies for a real-time DSS that relies on limited speech input based on standardized practices for triage assessment, such as questionnaires, are considered, with classification algorithms from the research assessed for this objective.

2.1. Navigation: Path Planning; Localization and Mapping

Simultaneous Localization and Mapping (SLAM) [4-10] with Kalman filter [4]; KNN [11] and cover trees [12]; Ant Colony Optimization (ACO) [13]; D* Lite [14]; Rapidly-Exploring Random Belief Trees [15]; and MIST [16] are applied for path planning in autonomous UAV indoor flight. SLAM techniques construct an environment map while simultaneously determining the location of the UAV within this map. ACO is implemented toward path optimization [13]. Both ACO and D* Lite utilize grid-based mapping and examine possible alternative paths in-flight [13, 14]. Rapidly-Exploring Random Belief Trees applies trajectory vectors to then examine alternative paths [15]. Localization and mapping are segregated in a method coined MIST, to reduce the computational load on the on-board processor [16]. Monocular Image Space Tracking (MIST) creates a map of the landmarks for pose tracking and occasionally sends the map to a ground station for smoothing and mapping [16]. Path planning algorithms primarily use camera technologies [4-10].

SLAM has shown utility for UAV path planning, map generation and localization [4-10] in dynamic, intricate and large-scale environments, primarily utilizing vision sensors. External location markers distributed within the environment have been used [6] to orient the drone using monocular SLAM. The Kinect device is also used to capture RGB-D images for unstructured indoor and outdoor environments in 3D which are then converted to greyscale, smoothed with a Gaussian kernel and a FAST (Features from Accelerated Segment Test) detector to extract depth features from the Gaussian filter [6]. UAV movement relative to its environment is estimated from successive image frames and features are matched for consistency [6]. Parallel Tracking and Mapping (PTAM) is used for UAV camera-based pose tracking and a metric scale estimation scheme to transfer up-to-scale position to metric form is introduced with a scale estimator that optimizes a cost function based on altitude measurements and forward facing visual measurements, for navigation and control [4, 10]. Kalman filters are used [4, 9, 10, 17] for tracking lateral velocity and position [4], and for landmark estimation as tree structures [9, 17]. A PID controller in [4] uses the results of velocity and position for navigation and an on-board attitude controller stabilizes roll and pitch angles of the UAV, yet depth measurement and scale estimates require off-board processing. iSAM [7] features Probabilistic Modelling with QR Factorization to reduce calculation complexity of other SLAM-based methods. When a new measurement arrives, instead of re-calculating the matrix factorisation, the square root factor is directly updated, enabling real-time processing. iSAM2 [8] replaces Probabilistic Modelling with Graphical

Modelling, improving algorithm accuracy by using Bayes tree data structures to generate 2D environment maps. Monocular SLAM with Extended Kalman Filter (EKF) [4] offers superiority over other SLAM-based methods in producing indoor 3D maps for path planning due to comparatively higher levels of accuracies and issues such as rapid changes of camera FoV are overcome using the Inertial Measurement Unit (IMU) data fused with processed camera images.

He *et al*. [13] develop a modified version of the ACO algorithm to provide flight path planning for UAV devices, overcoming shortcomings of the ACO algorithm. Their algorithm applies the action of separate ants (with each ant looking for direction) in a colony represented by an array, and then iteratively determines the best path [13]. However, major drawbacks such as slow rendering speed and lack of pheromone guidance cannot be ignored. He *et al*. [13] provided an enhanced version of the ACO algorithm, which shows promise for map formation and path optimization, yet algorithm efficiency and smoothing must be further addressed for it to prove useful in real-time. Rapidly-Exploring Random Belief Trees (RRBT) [15] defines discrete time descriptions of system dynamics, the initial state with some uncertainty and risk tolerance for possible trajectories. A cost function is generated using the Kalman Filter for each path and the RRBT then creates a set of vertices and edges of a tree graph, where the vertex has a state, the state has a belief node and each node has a state estimate covariance [15]. Nodes corresponding to unique paths are evaluated by the algorithm which returns the best path [15]. Research results showed accuracy of method, yet complexity and speed were not tested performance criteria [15]. The D* Lite algorithm is founded on the Life Planning A* (LPA*) algorithm yet it uses a heuristic approach for reusing information from previous iterations [14]. The LPA* algorithm calculates the shortest path on a grid map and adjusts the path based on the new input during execution [14]. It relies on a similar approach to graph formation, defining vertices and edges, as in RRBT. The shortcoming of the LPA* algorithm is in its assumptions concerning the environment, which relate to edges and costs [14]. D* Lite avoids these assumptions and therefore offers suitability for unknown environments [14]. Further, it begins its search from the goal cell towards the start cell, removing restrictions on the graph vertices and edges [14]. D* Lite is comparatively more efficient than A* and D*, requiring less vertices to calculate the shortest route, particularly in larger map dimensions [14].

Issues such as communication with a central server for position estimation [12] and maintenance of quadcopter altitude [12] need to be resolved for localization, mapping, and navigation, considering the high processing requirements of a multi-functional drone such as in this application. Localisation and Mapping will not be split into two separate components, as in MIST [16], but rather computed simultaneously, as in PTAM. ACO requires less iterations than RRBT to obtain the shortest path, making it a faster option. Monocular SLAM [4, 10] coupled with camera-sensing technology is best suited for path planning, including localization and mapping, to this application as it uses the Kalman filter to measure state in real-time, with fast processing capabilities and provides accurate results irrespective of fast-changing camera FoV. Real-time processing combined with high accuracy is a requirement for this application, due time-critical yet processing-intensive task requirements for the UAV including: localization and mapping, navigation and flight control, collision avoidance, patient location, recognition, querying, health assessment and actioning.

2.2. Navigation: Flight Control and Stability

Control and stability algorithms are introduced to enable flight dexterity in indoor environments, including dedicated algorithms for tuning UAV PID controller [18-20]; Fuzzy Logic Controller (FLC) [21, 22]; and Back stepping Controller [23]. Maintenance of stability during cases of emergency, such as propeller loss, is addressed [24]. The relationship of stability with autonomous navigation is considered [25] and techniques to achieve this relationship are evaluated [22, 26]. For sensor input, vision-based sensors including camera technology is mostly used [25-28], for pitch and roll estimation [28], height, angular condition, velocity and space orientation [25]. Laser and infrared are not as widely or effectively utilized, yet ultrasonic proves effective with an Inertial Measurement Unit (IMU) [27] for position, speed and yaw input to control and stability algorithms [29, 30].

PID controllers are effectively applied to control quadcopter rotational motor speed for system stability [18-20]. For the tuning of the PID controller, the authors use the Pole Placement Method, which is attained by identifying the transfer function determined by the input and output variables of the UAV system that is to be controlled [18]. For a UAV system, four PID controllers are proposed to give the best stability results [18]. Each angle of attitude will have a specific PID controller (pitch, roll, and yaw), along with the altitude. The PID controller associated with the pitch gives an output that would adjust the front and back motors (front-increase), while the controller's output for the roll will modify the left and right motors (right-increase). The PID controller for yaw will then be responsible for rotation, while the controller for the altitude adjusts for ascending and descending flight control [18]. Research findings reveal the stability of an UAV can be demonstrated through the use of a customized PID controller, to define the pitch and roll movements of the quadrotor [18]. The Ziegler-Nichols Method can be applied for PID controller tuning, implemented using either: the oscillation method or the reaction curve method [20]; the former is only applicable for open-loop stable plants [20]. The Ziegler-Nichols reaction curve method is commonly applied and enables simple, fast and accurate PID controller fine tuning for flight control and stability compared to the Pole Placement Method [20]. The former is considered for PID flight control in this work.

In [24], fundamental principles of dynamics and kinematics are applied by the authors to provide viable control of a quadrotor, to maintain stable, accurate operability when one or more propellers are completely damaged. An algorithm for quadcopter trajectory generation and flight control, that directly comprises the dynamic restrictions of the quadrotor while executing real-time route planning, has been developed by Hehn and D'Andrea [31]. Feedback control on planned trajectories is achieved based on initial conditions of the quadcopter's position, velocity, and acceleration [31]. However, a set limitation exists on accelerations allowed for each coordinate and as such, the algorithm may not be sufficient for acceleration limit variations. Problems associated with dominant aerodynamic effects are not overcome; notably, the vehicle rises when decelerating from high speeds [31]. The dynamic model [31] offers a promising methodology yet practical performance accuracy issues require further improvement.

A novel Cross- Entropy Optimization (CEO) -based FLC for Fail-Safe UAV is implemented [21, 22] with a Robot Operating System-based FLC and a FLC training framework integrated with CEO in MATLAB Simulink. The FLC used has 3 inputs (yaw error, its integral, and its derivative) and one output member function; using CEO, the scaling factors were optimized on Simulink [21, 22]. However, the hardware consists of the Parrot. ARDrone with camera and on-board IMU in which the software running on the microcontroller is not easily modifiable for customized control [21, 22].

An optimized Backstepping Controller (BC) is developed by [23], the paper uses Particle Swarm Optimization (PSO) to optimize the parameters which are initially chosen arbitrary. The control law is derived from tracking error and using the Lyapunov Equations, it is optimized using PSO. PSO is a population-based search algorithm that assigns each particle in the population to a possible solution and looks for the overall best solution in the population [23]. Simulation results showed accurate trajectory tracking and stability, however, the controller relies heavily on the quadrotor dynamics and assumptions about the quadrotor; the latter including assumptions of rigid body dynamics, symmetrical structure, rotor dynamics are relatively fast and can be ignore, aerodynamic effects can be ignored at low speeds and the center of mass and body-fixed origin coincide [23].

Flight control through modified PID control [20] with ultrasonic sensor input [29, 30, 32, 33] and an IMU [29, 32] is selected for this application over fuzzy control [21, 22] due to advantages in real-time response and accuracy of the former approach. While the Backstepping Controller offers promising results for UAV stabilization [23], underlying UAV assumptions and quadrotor dynamics may make it a less accurate, and more dangerous, solution when attempting to locate the patient for querying, indoors. Accurate stability is essential for real-time indoor flight where human movement and interactions are apparent. Camera input may be merged with ultrasonic sensor and IMU data for environment position input to the controller for more accurate flight control and stability.

2.3. Navigation: Obstacle Detection and Avoidance

UAV operability for collision detection and avoidance can be facilitated with algorithms that utilize ultrasonic sensor information [29, 30, 32, 33], image processing strategies [21, 26, 34], sonar or laser data [21, 22]. Results of these are input to avoidance algorithms that apply state machines for classification of object distance [32] and PID control for maintaining distance from an identified object [29, 30, 32, 33]. FLC by CEO also enables collision avoidance [21, 22].

State Machine Method applies a collision avoidance module to divide the environment into multiple zones which are user-defined, according to obstacle proximity to the drone [29, 32]. Environmental information is first ascertained and the state of the quadcopter determined [29, 32]. Initially, the quadcopter is at state 0 and if no object information is detected through ultrasonic sensor input, within a specified range of the quadcopter, it is in a safe zone state of 1 [32]. Any object detected within the range will switch the quadcopter to state 2 [29, 32]. The corresponding pitch or roll angle towards the obstacle is limited depending on the measured distance, reducing the speed of approach to a detected object [29, 32]. In the dangerous zone, state 3 is activated and the distance to the obstacle is controlled using a PID controller, preventing a further approach to the obstacle [29, 32]. In comparison to collision avoidance strategies that use camera image data, the method costs less and adds less weight to the quadcopter system, further ultrasonic sensors are not adversely affected by light or in a diaphanous environment. Ultrasonic technology finds difficulty sensing low density objects at long range and the resolution of detected obstacles may also be low. To overcome the issue of low resolution of detected obstacles, multiple sensors can be used to increase the resolution [33].

Fuzzy Logic Control (FLC) may be applied for obstacle avoidance [21, 22]. This method can receive images from camera technology for processing, to detect objects through color recognition; using a continuous adaptive mean shift (CamShift) algorithm to detect the center of the object [21]. The output of the detection module is then passed to the FLC to modify the trajectory of the UAV through yaw-driving commands [21, 22]. The system is optimized using CEO through tests with the ROS-Gazebo simulator and compared against the algorithm running in real-time on the Parrot AR.Drone; the comparison revealing only a small error between the simulator results and those of the Parrot AR.Drone [21, 22]. One identified problem was that the CamShift occasionally suffered from changes in the color distribution over time but this can be addressed by dynamically adjusting camera sensitivity to the changes in light distribution [21, 22].

State machine approach [29, 32] utilizing multiple ultrasonic sensors [33] promises better collision avoidance in an indoor environment, combined with a PID controller [29, 30, 32, 33], compared to FLC with image sensing [21, 22]. Within a close-proximity, indoor environment with possible human movement, ultrasonic-driven algorithms for real-time collision avoidance combined with PID control [29, 30, 32, 33] and an IMU [29, 32] show greatest promise due to fast, accurate ability to quantify distance and direction of movement of obstacles relative to the UAV.

2.4. Patient Recognition: through Voice- and Image-Recognition

2.4.1. Voice Recognition

Speech Recognition (SR) is applied in a variety of applications, within aerial robotics, for voice processing in real-time applications related to Air Traffic Control (ATC) [35-37], conversion of speech signals into control codes [38], and subsequent decision making [39-42]. SR hardware solutions [36-39] and novel algorithms [35, 38-41, 43, 44] are proposed in the research in real-time robotics, such as in the use of natural language communication commands to drive robotic movement [39]. SR hardware solutions are combined with class-based and dynamic language models; the former sorts words into classes based on their morphological and semantic features [38], while the latter considers the degree of recurrence of the word in the recorded history of usage to identify input keywords [37]. An ATC SR model is proposed for ASR and controller event detection, enabling automated analysis and interpretation of ATC voice interactions [36]. Input recordings are taken by a VoIP recording system [36]. ASR is applied for text broadcasting to reduce the rates of misunderstandings that occur between an aircraft pilot and ATC, such as in communication errors associated with non-native English speakers and also congested exchange channels [37]. ASR systems reveal around 99% accuracy when tested in ideal factory environment but prove to be of little use when faced with ambient noise in real-time [37]. A hardware and software solution is implemented for real-time user-robotic interactions *via* SR resulting in robot motion through user initiated commands [39]. The required constituents of such a system are identified as: a robotics module and active SR components, integrated and with the ability to initiate and interactively control robotic movement through speech-driven commands [39]. Research reveals that hardware-based systems enabling acceptable speech detection rates for real-time applications have variable results [36]; while hardware-centric systems show high accuracy errors in SR within ATC [37], other systems show improvement; in ATC voice communication an event detection rate (EDR) of around 70% in both flight en-route and approach communications is achieved [36]. Results of the hardware and software solution in [39] reveal instability issues due to noise and/or lack of user clarity of speech to the robotic interface.

Algorithms for Voice Activity Detection (VAD) include Long Term Spectral Divergence (LTSD), Multiple Observation Likelihood Ratio Tests (MO-LRTs) and Order Statistics Filter (OSFs) [42]. Approaches to overcome challenges of SR in noisy environments and reduce signal interference include modified versions of the Hidden Markov Model (HMM), applied extensively in the research [35, 40, 43, 45-47]; Mel Frequency Cepstral Coefficient (MFCC) [41]; Dynamic Time Warping (DTW) [41]; Neural Networks (NNs) for voice signal classification [38, 44, 48]; and Vector Quantization (VQ) [49-51]. In addition to problems associated with signal interference in a noisy environment, three major challenges in VR are word recognition within an extensive vocabulary, words with similar phonetics [37], imprecise pronouncement of consonants, tremor, hesitations and slow articulation [52], colloquial language, and age related degeneration such as vocal cord atrophy, muscle changes and calcification of laryngeal cartilage [53]. HMM is claimed to be the leading model in SR, while other strategies combine it with NN in a hybrid configuration that works on the principal of word-sound correspondence [37], as applied in [40] and [38]. Challenges for application of current methodologies include noisy input voice signals and continuous speech detection [40].

Strategies to achieve SR in noisy environments are examined [35, 42], with VAD applied to obtain high speech coding, low bit rate transmission and improved speech communication. Algorithms for VAD are compared in a survey describing a variety of assessment structures that process speech signal information, including LTSD, MO–LRT and OSF [42]. LTSD utilizes a long-term speech window based on the estimation of the Long-Term Spectral Divergence (LTSD) to track the spectral envelope of the speech so that a decision rule can be formed between the speech and noise [42]. MO–LRT aims to improve the decision rule through the incorporation of several observations to statistical testing [42]. OSF applies Multiband Quartile Estimation (MQE) Signal to Noise Ratio (SNR) to improve difference in speech caused by fricative sound through the complementary information it gives [42]. Mohamed *et al*. [35] examine two models for the analysis of SR systems in noisy conditions, aimed at stacking the elements of clean and boisterous channels to form a new, enlarged space comprising measurable models of a SR system. These factual models are interpreted for the prediction of the clean speech components from the noisy feature set.

HMM is identified as an effective mathematical tool in SR that aids in modelling speech time series [43]. HMM operates as a variant-limited state machine, with an arrangement of hidden states wherein each state provides an output with certain likelihood, transition probabilities, initial state probabilities, output probabilities of which initial state is not recognizable, and an alphabet as output [45]. HMM for SR is applied with algorithm improvement through application of the Forward Algorithm (to calculate output probability), Viterbi Algorithm (to determine best state path) and Baum-Welch Algorithm (for determining the transmission and emission matrices) [40, 43, 46]. The process of SR involves feature extraction and feature matching, where each word in the vocabulary has a distinct HMM that acts as reference for subsequent word matching [40]. HMM can be effectively utilized to model units of speech that comprise a sentence, phoneme or word [45]. It provides an efficient mechanism to model the variation in the statistical representation of the speech signal, in the frequency and time domains [45, 47]. A major drawback of HMM applied in a real-world environment is the conditional independence assumption of HMM; self-supporting speech frames are independent of their neighbors and this may lead to misclassification [46, 47]. However the efficiency of the model in processing of speech signals and its speed of parameter estimation during voice training make it suitable for the real-time application [47], and may be improved by modification and combination with other strategies.

In order to match a voice signal with a keyword in a database whilst minimizing classification error, speech processing using MFCC is deployed [41]. The MFCC enables processing of a digitized voice signal through pre-processing, Framing, Windowing, DFT, Mel Filter Bank, DCT and Delta Energy and Spectrum analysis, to extract voice features, which are then sent to a DTW algorithm that selects the corresponding pattern from a reference signal in the database [41]. However, MFCC and DTW methods are applied in an environment that lacks noise interference [41].

ANNs offer a framework of interconnected data handling components that prepare and process data as a dynamic state response to external, changing inputs [48]. ANNs reveal their potential in their ability to ‘learn’ in problem solving, similar to the human brain [48], however in SR, speech training places demands on computational requirements as well as the incapacity to take in time sequences of speech signals, hence lengthened time sequences representing speech cannot be processed [46, 47]. For SR, a multilayer Feed Forward (FF) network using a Back Propagation Algorithm to minimize the mean square error between input and expected output reveals utility [48]. A filtering system for SR based on a Fuzzy NN (one in which membership criteria change dynamically with incoming data, for data classification) is proposed for background noise suppression [44]. The application, G.H.O.S.T, is developed for the purpose of providing SR for elderly and less able-bodied individuals in a smart home environment [44]. Another system designed for disabled citizens and also employing NN classifiers for voice pattern recognition aims to improve SR by the reduction of False Acceptance Rates (FARs) of keywords in voice-driven commands [38]. Compared with classical HMM and DTW, the NN classifier proposed in [38] revealed better accuracy of classification and speed. However, Forward, Viterbi and Baum-Welch Algorithms [40] may be applied to overcome the comparative shortcomings of HMM. An Adaptive Neuro-Fuzzy Interference System revealed an improvement in error rate for real-time speech processing in a noisy environment, in comparison to a commonly applied Least Mean Square (LMS) algorithm, in a series of tests conducted by the authors [44] using wired and wireless microphones to capture speech input subject to ambient noise.

VQ is a centroid model that maps a large number of vector space to a limited, discrete number of regions (clusters) in that space [49, 51]. The K-Means Clustering Algorithm or the Linde, Buzo and Gray (LPG) Algorithm can be applied for clustering and mapping of the vector space [49]. VQ can be applied in speech synthesis, coding and recognition, and may also be applied to obtain a semi-continuous SR system achieving similar results as HMM [51]. For SR, VQ is a text-independent model that analyzes spectral information with reduced storage [50] and reduced computation when comparing similarities of spectral vectors, making it efficient in obtaining discrete speech sound representations [50], particularly for real-time applications. The major drawback of VQ in SR is the loss of speech information due to quantization during the processing of the original speech signal irrespective of speech signal length [50], which reduces word classification accuracy.

Research findings indicate that HMM is the best approach for real-time implementation of VR in a noisy environment. For extraction and recognition of human speech, HMM is able to execute DTW, which enables real-time extraction. HMM reveals superiority in terms of speed and accuracy, in noisy environments, in comparison to VQ [49-51] and ANNs [38, 44, 48]. VAD [42], Gaussian Mixture Models with SSM and SHMM [35] will be adapted to decrease word error classification rates in the presence of noise (due to propeller rotation). HMM approaches do reveal utility for word detection and classification [40]; the model offers an efficient algorithm for state and parameter estimation and performs DTW automatically [43]. Algorithm modifications are proposed to overcome errors in evaluation, decoding and optimization of model parameters for voice signal sequence processing [40]. Since HMM faces issues in the evaluation of hidden state determination and learning, the Forward, Viterbi and Baum-Welch Algorithms [40] may be applied to overcome these challenges. Sensor technology involves microphone and speaker for VR, with wireless communication to an off-board processor for health-based DSS.

2.4.2. Image Recognition

Image Recognition (IR) algorithms are applied to images acquired from camera technologies for a variety of applications toward automatic facial recognition, such as in biometric identification [54], tracking for surveillance [55] and facial shape reconstruction [56]. Many of the existing solutions assume the convenience of frontal upright faces of similar size for processing [57], however in reality this is not the case, with varied facial appearances and complex, dynamic environmental conditions. Facial recognition systems which are dependent on standard face images are susceptible to misclassification of background areas as features defining the face. To counter this problem, a visual front-end processor is required to localize and extract the face region from the background. Given a still or video image, to detect and localize an unknown number of faces, algorithms for facial detection, segmentation, extraction, and verification are required, and within these possibly facial feature extraction from an uncontrolled, unknown and complex (comprised of several objects; moving or still) background. As a visual front-end processor, a face detection system should be able to classify a human face regardless of contextual illumination, orientation or camera distance. In this application, real-time requirements are imposed, as well as moving image series that may result in image blur. The image-based face detection methodologies relevant to this work are primarily: Linear Subspace Methods [58-60], Neural Networks [61], and Statistical Approaches [62].

Linear Subspace Methods address the problem of modelling faces by geometric formulation; allowing the detector to project a tested image onto a pre-existing subspace and determine if it is similar to that subspace [58-60]. A manifold is then computed in $\square^n$ with vector space, $\square$, comprising images containing n pixels, from the most significant components of the general face. Sung *et al*. [58] developed a method in which the detector is primarily focused on discerning between faces and anti-faces. A bootstrapping strategy is applied for creating an anti-face training set consisting of only the most meaningful non-faces [58]. Other approaches to separating faces and anti-faces in an image space are applied [59, 60], which are based on the support vector machine, with a selected manifold defining separation criteria, implemented using quadratic programming and exploiting properties of the models' kernel functions. Although the scheme offers simplicity in implementation, the computation is quite burdensome and not suited for real-time facial recognition.

Artificial Neural Networks (ANNs) are implemented for facial detection [61] where the NN contains there types of hidden units that examines sections of the image space: one set of units for quadrants of the 20×20 image, one set for quadrants of the quadrants, and one set for looking at overlapping horizontal stripes of the image. Certain hidden units will help detect certain facial characteristics [61]. To train the NN on an image set, a large number of images containing faces must be used. The locations of these feature points are averaged over the training set, then warped to coincide with predetermined points [61]. Each face training image can then be aligned to the mean as the optimal solution to an overdetermined system [61]. ANNs are a powerful tool to solve facial recognition problems, due to their robustness and effectiveness in different environment conditions. However, customization of design to the application and extraction criteria are required as well as parameter fine-tuning and algorithm training.

Statistical Modelling is implemented by representing visual attributes with wavelet coeffients [62]. An image can be reconstructed from its transform with a wavelet coeffient set that has the same size as the image itself, and in [62], three filter levels are used which give 10 image sub-bands. This representation enables joint modelling of image data which is localized in space, frequency, and orientation, and from this information, a histogram-based face detector is constructed using Bayes' decision rule [62]. Adaptive Boost (AdaBoost) is a machine learning algorithm for boosting (that is, finding a highly accurate hypothesis by combining several 'weak' hypotheses, each with moderate accuracy) used to compute each part's likelihood of belonging to the detected object [62]. The final decision regarding facial recognition is made by multiplying the likelihood ratios of all the parts together and testing the result against a predefined threshold [62]. This method [62] is computationally expensive and suffers from the usual shortcomings of straightforward correlation-based approaches, such as sensitivity to face orientation, size, variable lighting conditions, background clutter, and noise.

Viola Jones Detector applies the concept of an "integral image" combined with the Haar wavelet representation, with the classifier trainer performed with the AdaBoost method, to detect faces at 15 fps [63]. An attentional cascade is used consisting of low-feature-number detectors based on a natural extension of Haar wavelets [63]. For each pixel in the original image, there is exactly one pixel in the integral image, whose value is the sum of the original image values above and to the left [63]. The integral image can be calculated swiftly, and significantly cuts down computation [63]. Training the attentional cascade is similar to other training methods such as in [58], for basic bootstrapping, but is geared toward the progressive nature of the attentional cascade. This represents an improvement in computation time over previous implementations of face detection algorithms and by far is the most efficient algorithm offering high accuracy in results, for face detection.

The Viola Jones Detector [63] offers straight-forward implementation promising high accuracy for real-time image processing, for patient detection and classification, in the proposed work. In comparison to other strategies for IR [58-62], it offers a robust, real-time face detection method for patient recognition and classification in aerial navigation. Patient detection and recognition is proposed using a hybrid approach, combining the Viola Jones Detector [63] for IR, a modified HMM [40, 35] and VAD [42] for VR, and in conjunction with customized ultrasonic sensor strategies for movement detection and classification.

2.5. Expert System for Patient Health Assessment

Decision support for mental and/or physical disorders with primary focus on artificially intelligent server-based engines integrating has been achieved in a limited capacity. These include rule-based expert systems [64-67], implemented with decision tree classifiers [64], heuristics [68], fuzzy logic [69, 70] and neural networks [70], with hybrid approaches suggested [70]. While computerized DSS's have been developed for cancer care [65], blood infections [66] and differential diagnosis [67], research that is focused on the design and deployment for a fully-automatic, drone-based client-server decision support using querying for health assessment has not yet been achieved.

2.5.1. Rule-based Expert Systems: Decision Tree Structures

Rule-based expert systems using decision tree logic have been designed and implemented for dedicated clinical care [64-66]. MYCIN applies a rule-based expert system to diagnose and recommend treatment for blood infections; assisting clinicians in their choice of antibiotics for bacteremia or meningitis. The clinicians enter information regarding patient history, physical findings and laboratory results into the system, which then provides patient-specific recommendations for antibiotic coverage [66]. INTERNIST-I is a rule-based expert system that uses observations of patients to classify various states of disease [64]. INTERNIST-I was initially designed in 1974 and links diseases with symptoms using a tree-based structure that performs a complex diagnosis for general internal medicine [64]. ONCOCIN was one of the first DSS's which attempted to model decisions and sequencing actions over time, using a customized flowchart language for the implementation of a rule-based medical expert system [65]. ONCOCIN was designed to assist physicians with the treatment of cancer patients receiving chemotherapy [65]. Classification accuracy of these systems ranged from 69% [66] to 72% [64] although human expert classification of infectious diseases were less accurate [66]. Further, processing time was slow; with 30-90 minutes on average per consultation [64], which is not effective for immediate, real-time triage assessment. Improvement in classification accuracy, processing time and removal of human interaction (i.e. automating the system entirely) is therefore required.

2.5.2. Rule-based Expert Systems: Heuristics

A semi-automatic mobile DSS, iTriage, is introduced and subjectively validated through testing the system on triage nurses and questionnaire evaluation, to provide a supplementary IT-based tool for triage care. A multicriteria heuristic algorithm is designed, over a rule-based expert system [68]. Nurse input is required for selection of medical attention category best matching patient needs, attribute selection that qualifies the identified need and a confidence level for their triage decision [68]. For an autonomous drone-based solution, human intervention for assistance of the DSS in classification is not an option. Triage scale categories and physiological discriminators, as documented in the study [68], provide useful guidelines for human-based triage classifications, yet drone-based querying will require translation of some indicators and addition of others, to enable classification based yes/no health status querying.

2.5.3. Fuzzy Logic Classifiers

Fuzzy Logic Classifiers (FLCs) have been applied for medical applications [69, 70], although these require internal imaging for algorithm input, while non-invasive methods of assessment are applied in the proposed work. In [69] a selection of cancer types including breast, lung and colon are classified and compared using the Mamdani model and a fuzzy logic model. Algorithms are programmed in C# on the Visual Studio. Net 2010 platform [69] and techniques compared using Receiver Operating Characteristic (ROC) analysis showing higher accuracy of specificity and sensitivity as well as lower false-negative rates, leading to greater overall algorithm accuracy for results achieved from the FLC.

In addition to features extracted through fuzzy logic applied directly to the images, other risk factors are ascertained for patient classification [69]. In the breast cancer model: sex, age, genetic status, menarche age, menopause age, first childbirth age, alcohol consumption, and nutritional habits are determined as factors for cancer risk [69]. In the lung cancer model, sex, age, skin tone, smoking, age of starting smoking, passive smoking environment, occupational status, living environment, genetic status, economic status, and nutritional habits are determined as factors for cancer risk [69]. In the colon cancer model, age, genetic status, cancer history, inflammation status in the intestines, physical activity status, weight status, smoking, alcohol consumption, and nutritional habits are determined as factors for cancer risk [69]. Of relevance to this study, risk factors for levels of patient assessment in triage care need to be determined, for construction of an initial patient profile.

2.5.4. Fuzzy Cognitive Maps

A Fuzzy Cognitive Map (FCM), integrating aspects of fuzzy logic, neural networks, semantic networks, expert systems and other computing strategies, is implemented to categorize medical requirements determined by triage in the Emergency Department, for elderly citizens [70]. Physical concerns for the elderly can be numerous, different from younger patients, and may co-exist with cognitive and functional problems [70]. As identified by the authors, in addition to medical and laboratory examinations, questionnaires as used to assess the status of a patient, such as the Questionnaire Identification of Seniors at Risk tool that enables functional and mental status determination [70]. The FCM operates on a structure that uses fuzzy signed directed graphs with feedback, enabling modeling of complex nonlinear, dynamic systems that provide an interconnected network of interrelated entities, distinguishing causality between concepts [70]. The Competitive Fuzzy Cognitive Map (CFCM) has two types of concepts: diagnosis and factor, where the latter are inputs such as those from patient data, symptoms, experimental tests, and the former are outputs where their values are possible patient diagnoses [70]. The weights and network connections establish the degree to which one concept influences the other and interconnections are implemented using if-then constructs. Categories of severity are established (emergency/urgent to non-urgent) [70]. Decision factors are first identified through documented methodologies and expert questioning, and then the importance weight and specific weight of the decision factors are established [70]. The identified factors and weightings are then used for membership functions in the CFCM for patient classification into one of the 5 ESI triage levels [70].

Neural Networks [70], rule-based expert systems [65-67], fuzzy logic [69, 70], heuristics [68] and decision tree classifiers [64], or a combination (hybrid) [70] show utility towards an intelligent, server-side medical DSS for real-time response. However, for this application, VR and IR strategies must be applied for speech extraction and patient identification, as input to the classifier which must be designed based on clinical practice, but limited to yes/no querying for a fully automated drone solution. A hybrid approach for dynamic rule-based classification, incorporating fuzzy NNs and decision tree logic, is best suited to meet the objectives and functionality required by this study. Existing medical protocols and criteria for triage assessment must first be examined to identify associated weights for inclusion into a dynamic, computerized classification design structure that enables yes/no querying. A combined approach, as in [70], that utilizes fuzzy decision logic and a decision tree structure, but is dynamic and operates in real-time with no human input, is desired. Validation in terms of accuracy, consistency and effectiveness of decision support is then required.

3. OUR PROPOSED SYSTEM

3.1. Hardware Solution

The literature indicates that several commercial UAV solutions are available, but these lack the ability to program and control the drone using customized algorithms. Further, sensor requirements vary depending on application. Essential hardware requirements for drone assembly for the proposed application are identified as: mechanical components, comprising motors, the frame, electronic speed controllers, propellers, propeller adapters. The embedded system is composed of the microcontroller (PIXHAWK) to run path planning, control and stability functions, as well as process sensor data and feedback from the DSS. Sensors for path planning, flight control and stabilization include a camera, multiple ultrasonic sensors, IMU as well as an accelerometer, magnetometer and gyroscope. Power needs include battery chargers and power distribution. Transmitter/receiver units are required to aid in controlling the aerial manoeuvre manually (for testing and safety) and to transmit and receive telemetry. Communication *via* WiFi is essential to enable client/server data transmission between microcontroller and server-based DSS; here, the XBee module is identified for installation into the frame base to ensure long range communication and so that voice and image data from the user can be sent back to the computer wirelessly. Since GPS does not work accurately indoors, ultrasonic sensors and camera technologies are utilized for indoor navigation. Ultrasonic sensors are tested to have a wide beam that reflect off surfaces, revealing utility for proximity sensing (distance determination), autonomous navigation and for human movement detection. The Matbotix Sensor is a popularly used commercial sensor for this purpose. Figure **1** provides an overview showing basic hardware components, embedded algorithms and sensor data input driving data flow between modules.

Images collected by the on-board camera are input to the path planning function running on the Pixhawk microcontroller, as well as the IR function. The data output from path planning, in addition to ultrasonic sensor input and IMU data, as well as SR and IR output, are input to the PID controller enabling in-flight control and stability. Sensor values invoke changes in values of the Electronic Speed Controllers (ESCs) driving motor (hence rotor) speed since sensor information is processed by the on-board processor. Ultrasonic sensor data is input to the state machine

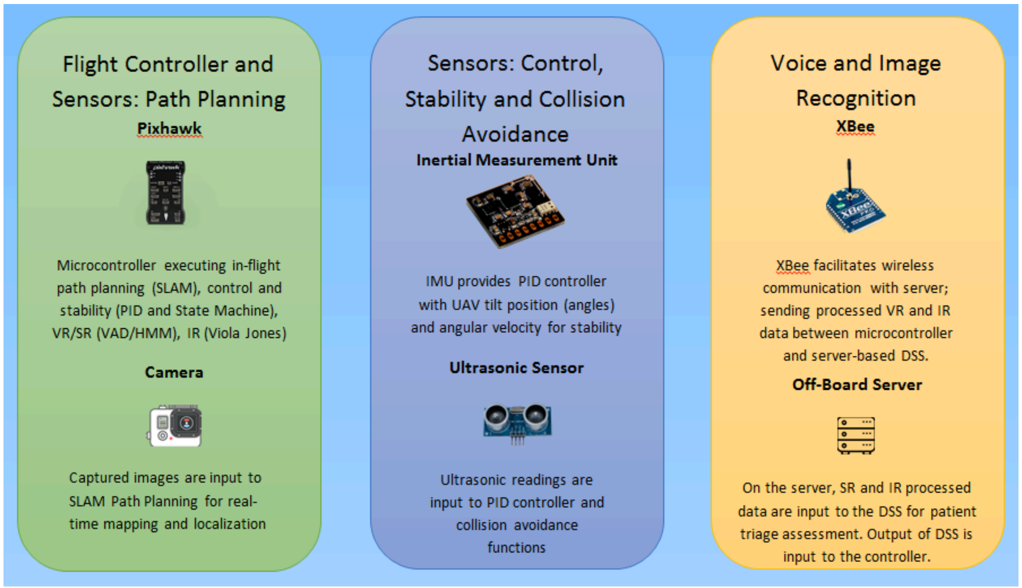

Figure 1: Major hardware components including microcontroller and sensors, driving and running major system functions.

running on the microcontroller for collision avoidance, the output of which is also input to the flight controller. Microphone pick-up is input to the VR function, which is input to the SR function, on the microcontroller. Data processed from the SR and IR functions are transmitted *via* the X-Bee Wi-Fi module to a server (PC) as input to the DSS, as well as to the microcontroller; for the latter, if a patient is recognized the UAV will fly toward them. Outputs from the DSS are sent back to the microcontroller for processing; resulting in speech output (through text-speech module) *via* an on-board speaker and/or UAV movement. The system components are assembled (see Figure **2**) and controlled flight achieved using a fine-tuned PID controller.

Figure 2: Health buddy UAV hardware system assembled and operable. Note four motors and rotors, with microcontroller housed in frame.

3.2. Design of the Algorithms

The research literature introduces a variety of techniques for the attainment of quadrotor navigation, path planning, stability and flight control, collision avoidance, as well as for medical decision support (refer Section 2). While several methods address the independent research challenges associated with indoor flight and those of a decision support system, for the specific application involving patient recognition during GPS-denied flight, requiring real-time speech extraction, analysis and patient-drone querying through a remote server-based DSS, new challenges emerge which place requirements not only on hardware design (weight restrictions, customizable control) and sensor selection (detection of still or mobile objects, human recognition and patient identification, and querying), algorithm adaptation must consider these new system objectives. Autonomous computerized DSS's for chronic care and health assessment do not currently exist, and coupled with a mobile, autonomous drone indoors and limited to speech-based patient querying, challenges compound, causing restrictions and creating new criteria for technical considerations and research methodology.

PID control integrated with ultrasonic sensors and camera technology enables customized, fine-tuned indoor flight control and, combined with IMU data, stability. PID control for this application is selected over other methods due to its advantages in real-time response and ability to combine with collision avoidance modules, including state machine logic, as well as to detect movement. In a highly constrained indoor environment, with possible human movement, ultrasonic-driven algorithms for real-time collision avoidance are best suited to this application, due their ability to quantify distance and direction of movement of obstacles relative to the UAV accurately and swiftly when compared to other methods such as FLC. Patient detection is paramount for this application and drone flight control is directed toward this goal whilst maintaining collision avoidance. PID control also enables input from VR/SR and IR functions, for patient recognition. Monocular SLAM is selected for path planning with the Kalman filter for real-time state measurements and generation of 3D environment maps, despite fast-changing camera FoV due to drone movement.

For real-time patient recognition VR and IR strategies are both proposed. VAD enables VR while modified HMM with Forward, Viterbi and Baum-Welch algorithms offer real-time SR in a noisy environment. The Viola-Jones face detection algorithm offers real-time IR possibility for patient facial detection, promising high accuracy for real-time image processing in comparison to other strategies for IR. Once detected and identified, SR output is input to a hybrid DSS. This hybrid model is to be designed using a combination of Neural Networks, fuzzy logic and represented as a weighted network, where triage assessment weights are constructed both dynamically, based on patient querying, but initialized from established standards and questionnaires documented in clinical practice. Patients are queried in real-time by the drone and the classifier must be designed for yes/no responses.

4. CONCLUSIONS AND FUTURE WORK

Most UAV applications are not combining human detection and recognition strategies, yet the added complexity of this not only adds much data for processing in real-time, but the control and classification algorithms must be redesigned; this involves development of new models that contain combine and interpret data from image, voice, movement and position within a noisy, constrained and GPS-denied environment. Further, new hybrid classification algorithms within the DSS must be developed based on clinical practice, and multi-sensor driven input, but restricted to in-flight (mobile), non-invasive assessment (voice and image –activated). It is not a matter of integrating the components to overcome the individual challenges, but, upon system integration and system objectives, new control and classification algorithms must be developed and adapted to meet the end goal of autonomous UAV patient healthcare. Future work focuses on adaptation and extension of most suited algorithms identified as: PID, State Machine, SLAM, VAD, HMM, Viola-Jones Detector, Hybrid Neural-Network and FLC, and hardware, as examined extensively in this study, toward new model designs that meet the unique criteria of this work.

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