Quantifying agitation in sedated ICU patients using digital imaging

J. Geoffrey Chase, Franck Agogue, Christina Starfinger, ZhuHui Lam, Geoffrey M. Shaw, Andrew D. Rudge, Harsha Sirisena

1. Introduction

Patient agitation prolongs recovery, interferes with administration of drugs and therapeutic procedures, and decreases the safety of the patient and medical staff. While sedation is administered to maintain patient comfort, most sedation in the ICU is administered in addition to this amount in response to patient agitation [1]. The estimated yearly cost of ICU administered sedatives and/or analgesics in the US is US$ 0.8—1.2 billion [2]. However, current methods of assessing agitation are subjective and prone to error leading to over-sedation, and increases in cost and length of stay [2—4]. Therefore, a consistent, quantifiable,
and it is left to the nursing staff to remember the patient's needs with their own methods, and reassess the patient's needs with theirownmethods, which is detected from their personal expectations and patient history. Patients who lie quietly without moving, have neuro-muscular blockade, or are unable to communicate would exacerbate this problem, preventing any significant agitation assessment with these scales. Similarly, management of patient agitation is a significant problem in paediatric critical care units as well.

1.2. Proposed agitation assessment method

Patient movement currently plays the primary, if not entire, role in the assessment of patient agitation when the patient is reasonably sedated [12]. This large role is reflected in a study carried out to investigate nurses' assessment of movement and agitation in sedated patients [13]. Hence, current agitation assessment can be dominated by the assessment of excess or undesirable patient motion. Therefore, it is proposed that measuring the power in patient motion over different time intervals can lead to a relative yet objective patient agitation scale. This approach can be extended to include multiple motion signals representing motion of different portions of the body, the limbs (arms, legs) and head in particular for this case. Moreover, the system must also be able to differentiate between patient motion and motion of the nursing staff working with that patient, which is detected from motion at the edges of the frame. Once measures of patient and nursing staff motion are obtained, a fuzzy inference system (FIS) can be used to differentiate them and classify the level of agitation by using medical experience and extensive observa-
tion to create rules from which a patient agitation level can be quantified. A FIS is used because the system dynamics of sedated patient agitation are essentially unknown. Clinically, a quantified measure of patient agitation also offers a method of improving sedation administration, as well as a platform for quantifying the effects of different sedative therapeutics in reducing patient agitation.

2. Materials and methods

There are four main aspects to the image processing required: (1) image capture; (2) motion sensing and power calculation; (3) quantification as a measure of relative patient agitation; and (4) determination of an agitation index using fuzzy logic.

2.1. Image capture

All video is taken at five frames per second (fps) using a digital camera. The individual frames are stored as AVI files on the PC used for image capture and then stored as bitmap images of 320 x 240 pixels (4/3 format) on the PC used for image processing. The bitmap files are converted from RGB (24-bit) to 256 shade (8-bit) grey-scale images to minimise computational intensity and processing. The process is done in two steps for this proof of concept research, but focuses on computational simplicity for eventual real-time practical implementation.

2.2. Motion Sensing

Typical regions of interest (ROI) for detecting motion are as shown in Fig. 1 for a simulated ICU patient. They focus on the limbs and head where agitation related motion is considered most likely. In addition to patient specific ROIs, edge regions are monitored to detect external movement due to medical staff who are constantly interacting with the patients. When movement outside ROIs is detected, and the movement moves into adjoining ROIs, the resulting reading is appropriately weighted until such time as the movement ceases. More specifically, the basic method presented splits the image into patient and nursing (edge) regions and determines a normalised measure of motion power in each. The method can also be extended to individually examine motion of specific body parts or areas of the patient, as defined in Fig. 1.

Prior research in this area has applied simple block comparison methods to detect motion [11,14]. The block comparison algorithm captures and quantifies movement by calculating pixel differences between successive frames to ensure minimal computational intensity. Since subtraction is computationally simple, the appeal of this technique is in its ability to process data quickly, a major requirement if this method is to be implemented real time. The resulting intensity values can then be further filtered or processed, as necessary. By comparing the results over multiple frames, it is possible to detect and quantify the magnitude of specific body part movements over time.

If $f_t$ is a frame that occurs in time $t$, with 8-bit (0-255) greyscale pixel values, $f_t(x,y)$, located at $(x,y)$, the pixel difference at times $t+1$ and $t$ is defined:

$$D_t(x,y) = f_{t+1}(x,y) - f_t(x,y)$$  \hspace{1cm} (1)

The sum power difference over the frame is therefore defined:

$$P(t) = \sum_{x=1}^{m} \sum_{y=1}^{n} D_t(x,y)^2$$  \hspace{1cm} (2)

where $P(t)$ is a single scalar index that can be used to compare frames and be filtered as necessary. Eqs. (1) and (2) can be applied to each ROI separately where $f_t(x,y)$ would represent only the pixels in the ROI. The value in Eq. (2) can also be normalised to the maximum possible value.

However, block comparison is easily influenced by pixel noise. Pixel changes from frame to frame that are not due to patient movement will cause false positive readings. Pixel 'noise' can be lessened by
regions of the frame. The correlation coefficient, \( \kappa \), between regions a frame to frame correlation image, or ROI within the image.

to measure the change between frames of a given motion that eliminates these effects is required. To achieve this task, a correlation coefficient that is normalized to eliminate these effects can be used to measure the change between frames of a given image, or ROI within the image.

To the normalized level of motion in both the patient and nurse areas a frame to frame correlation is made for the entire patient area and the edge regions of the frame. The correlation coefficient, \( r_k \), for each of these \( (k) \) regions is defined as the ratio of the covariance between frames over the combined variance of frame \( t \) and \( t+1 \).

\[
r_k(t+1) = \frac{\text{cov}(f_t, f_{t+1})}{\sqrt{\text{var}(f_t) \times \text{var}(f_{t+1})}}
\]

where “var” is the variance and “cov” is the covariance for the image frames, which can be expanded to define the correlation coefficient:

\[
r_k(t+1) = \frac{\sum_{xy} (f_t(x,y) - \bar{f}_t)(f_{t+1}(x,y) - \bar{f}_{t+1})}{\sqrt{\sum_{xy} (f_t(x,y) - \bar{f}_t)^2 \times \sum_{xy} (f_{t+1}(x,y) - \bar{f}_{t+1})^2}}
\]

where \( f_t(x,y) \) is the pixel value (0-255) at location \( (x,y) \) at time, \( t \), and \( \bar{f}_k \) is the average pixel value over the entire region, \( k \), with similar definitions for time \( t+1 \). The numerator is the covariance between frames for that region and the denominator is the combined variance. Note that the image frames are defined in Eqs. (3) and (4) for the given region, \( k \).

Eq. (4) presents a direct, normalized measure of the change between frames, presenting a clear measure of the level of motion. Therefore, bias due to changes in lighting or differences in camera distance or position that can influence the block comparison method is eliminated. The magnitude of \( r_k(t+1) \) approaches 0 when there is excessive motion because the covariance between frames is very low, and approaches 1.0 when there is little motion. Note that this value can be determined for the entire patient and nurse areas or combined over selected ROIs.

### 2.3. Relative agitation index (RAI)

Mathematically, the value of \( r_k \) in Eq. (4) can vary between \(-1\) and \(+1\), depending on the change in motion. However, the magnitude of the motion is typically measured by the variance between frames, which is represented by the coefficient of determination, \( R^2 \), over the range from 0 to +1, eliminating the phase shift information in the sign. As a result, a motion related agitation index can be defined.

\[
A_k(t+1) = 1 - r_k(t+1)^2 = 1 - R^2_k(t+1)
\]

where \( k \) is defined for the nursing, or edge, region, and/or specified ROIs. Therefore, \( A_k \) approaches 0 when \( R^2_k \) approaches 1, the motion is very low between frames. Similarly, \( A_k \) approaches 1 when there is extensive motion.

Using Eqs. (4) and (5), different combinations of correlation values for the patient and nurse areas can be measured in real-time. Based on experience and observation, these combinations relate to different activities, not all of which are agitation related. For instance, low patient motion RAI value and high nursing motion RAI value might indicate the nurses restraining the patient in severe agitation. In contrast, reversed values might indicate the nurse performing a task that is seen in both the patient and nurse areas with no patient agitation present. Hence, greater patient motion may be the

**2.4. Fuzzy logic quantifier**

Fuzzy mathematics is a very useful tool for classification and diagnostics problems where the dynamics of the system are not well known. Fuzzy system models rely on rules defined from logic built from observational data, rather than sharp formulas, to approximate the unknown dynamic behaviour. In this case, the dynamics are defined to range between 0 and 1 as a convenient decimal percentage. The result is a fixed neural network model that is derived from the fuzzy mathematics and rules defined, providing a measure of probabilistic likelihood of each membership function of a fuzzy set representing the likelihood of different levels of agitation (e.g., low, medium, high).

This neural network is not trained and is thus not a neural network in the traditional sense. It is merely a means of computationally expressing the
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Fig. 2 Patient motion fuzzy set membership functions where the x-axis is the patient input motion coefficient from Eq. (5) and the y-axis is agitation level.

rules and fuzzy mathematics, and is not integral to the method developed. Therefore, this application employs rules and time periods based on current medical treatment protocols and experience to define membership functions and rules. This process is called “fuzzification” where crisp, continuous data values are transformed to a discrete, fuzzy low—medium—high classification to be processed by the rules defined to quantify agitation.

The motion agitation index is derived directly from the video frame-to-frame correlation coefficients for the nurse and patient motions. Fuzzy logic is used to determine a single motion-related agitation index from these two motions. The patient ROI fuzzy set membership functions (MFs) are shown in Fig. 2 where the x-axis is the patient input motion coefficient from Eq. (5) and the y-axis is agitation level. The same sets are used for nurse motion.

Note that the MFs are not spread regularly along the signal input range because motion is measured via the correlation coefficients. This coefficient is equal to 1 if two consecutive frames are identical, however large motions from either the patient or the nurse will never decrease the correlation coefficient to exactly 0 because they do not cover the whole area and the area corresponding to the patient’s bed or background will remain unchanged. As a result the membership functions, which estimate low—medium—high agitation levels based on the correlation coefficient input are skewed towards zero. The thresholds set for these MF definitions are based on trial and error with simulated critical care patient motion using actors.

Given the MF definitions for both nursing and patient motion fuzzy rules, based on experience and observation, are defined to quantify an agitation index value. The rules, created using Matlab’s Fuzzy Logic Toolbox, are listed in Fig. 3. They determine, using fuzzy mathematics [16,17], the likelihood that patient agitation is low, medium, or high using the two inputs and MFs defined, and result in the fuzzy transfer surface shown in Fig. 4 that relates the two inputs and the agitation index output.

The final (0,1) agitation index in Fig. 4 output results from combining the fuzzy (low—medium—high) values and weights to return a crisp number in a process called “defuzzification”. This process is performed using fuzzy mathematics based on the rules and MFs defined in an inverse manner. Hence, Fig. 4 shows the transfer function of the entire fuzzy logic inference system from crisp input values to crisp output values, in between which the dynamics are defined by the rules and MFs. There is significant room for improvement in this proof of concept implementation, and the effectiveness of these rules and input definitions will be improved through further research and tests. Finally, standard texts can provide greater detail on fuzzy mathematics and its application [16,17].

Fig. 3 Fuzzy rules to define agitation.
2.5. Clinical trial procedure

The fuzzy logic rules and MFs were defined based on trial and error tests using simulated critical care patient agitation videos developed using volunteer actors. These simulated motions mimicked different levels of observed patient agitation, based on inputs from medical staff, and Fig. 1 shows a typical frame from that video. The current system was then tested on five critical care patients to prove the initial concept and overall approach. All trials were performed in the Christchurch Hospital Department of Intensive Care, with ethics approval from the Canterbury Ethics Committee. Patient consent was obtained either from the patient or immediate family member.

All critical care patients were receiving fixed concentration morphine (1 mg/mL) and Midazolam (0.5 mg/mL) solution to provide pain-relief and induce sedation. These patients were being weaned from sedation, prior to extubation, to best ensure that a range of agitation might occur. Patients with neuro-muscular blockade, head injury or morbidity were excluded. Agitation, as assessed by nursing staff, was recorded periodically using a modified Riker SAS with a scale of 0 (calm) to 3 (extremely agitated) [11,18]. The regular Riker SAS [6] uses the values 4—7 for this range, with 1—3 representing levels of sedation. The modified scale is more intuitive as it separates sedation and agitation scores, as only agitation levels are assessed for this research.

3. Results

The initial system was developed and tested using volunteer actors to obtain the transfer function in Fig. 4 before ICU testing. Fig. 5 shows the non-normalised power levels for high, medium, low, and (non-agitated) normal levels of simulated motion. It also shows a motionless response with the expected zero result. The x-axis is in frames, at 5 fps, so each clip is approximately 12 s and the y-axis is in non-normalised power level, as defined by Eq. (2) and summed over all of the ROIs defined in Fig. 1. As expected, the more significant the agitation the greater the power of the motion, which also matches the primary means of agitation assessment [12,13].

Figs. 6—8 show the results for three individual ICU patients whose agitation response across patients, as assessed by nursing staff, spanned the range from light to extreme agitation. The y-axis of the first two frames presents the normalised patient motion and nursing motions from 0 to 1, respectively. The y-axis of the third frame is the resulting patient agitation index in the range from 0 to 1. The x-axis is in minutes for each frame. The large figures in the third frame are nursing assessments of agitation using the modified Riker SAS, which were recorded using the data acquisition software designed for this trial. Each figure represents a small portion of the entire patient survey, which was typically 10—20h, where significant agitation was manifested and the nursing staff had the time to record Riker SAS assessed agitation.

Fig. 6 shows light level 1 agitation as assessed using the modified Riker SAS. Note that there are intervening periods of low measured agitation using the methods developed and the lack of nursing assessment here is assumed to be level 0 agitation, which does not require nursing attention. Note that the assessed agitation score is beginning to rise
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Fig. 6 Patient 1: patient (frame 1) and nurse (frame 2) correlation coefficients and resulting agitation index (frame 3) for a selected 30 min period. Nursing assessed agitation is shown over the agitation index using the Modified Riker Scale.

at the end of the 30 min sample as evidenced also by increasing amounts of motion for both patient and nurse, ending with the nurse restraining the patient.

The results for Patient 2 are shown in Fig. 7 with a higher and more consistent period of assessed agitation. In this case the patient was calm and then began to manifest a growing level of patient agitation. This agitation was treated with some additional sedation and a calm state restored. Note that the greater nursing motion around 20–25 min is due to the nursing staff checking on the patient and performing other tasks. Hence, higher nurse motion and low patient motion are appropriately differentiated by the FIS in this case.

The results for Patient 3 are shown in Fig. 8. This patient experiences a significant and extended bout of severe agitation that requires a great deal of restraint as noted by the excessive correlation coefficients for both patient and nursing staff. The assessed agitation levels reflect this severity in the assessments of levels 2–3 by the staff over this 20 min period. Note also the very rapid rise in agitation from a calm state, assessed at 0, over the first 10 min, illustrating the rapid changes that can occur in these patients.

Finally, Fig. 9 shows the agitation level assessed using patient motion, as well as for assessments made using other physiological signals for the same patient in Fig. 8, but for a second time period where all three levels of Riker SAS agitation were observed. In this case agitation levels assessed using heart rate (HR), systolic blood pressure (BP), heart rate variability (HRV), and blood pressure variability (BPV) are also presented using the methods in [11,19]. The final frame shows the combined agitation levels determined from the fuzzy mathematical combination of MFs for each metric before the output of the final crisp patient agitation value.

As a result, a given metric is only dominant in the final frame when all the others are low and/or falling. Note also that the motion assessed agitation value appears to correlate well with the physiological measurement based metrics, both of which have been independently shown to correlate with subjective nursing staff assessments in
proof of concept studies [11,19]. These results indicate that these two approaches to quantifying agitation, based on correlation with nursing staff assessment, also match, which should be expected and serves as an additional check rather than a formal correlation of the methods.

4. Discussion

Fig. 5 illustrates that the increased motion seen in simulation of various levels of ICU patient agitation has power that can be directly correlated to patient agitation and used to develop rules about how to quantify that level of agitation. Figs. 6–9 show the results for three ICU patients that manifested differing levels of patient agitation spanning the 0–3 range of the modified Riker SAS scale. In each case, increasing levels of patient motion resulted in an increased agitation index. These increases correlated consistently and well with nursing assessed agitation levels. In addition, calm periods, where nurses noted no agitation and made no assessment, were not recorded as false positive results. As patient motion is often the primary input used in subjective assessments of patient agitation [12,13] good correlation indicates the effectiveness of the fuzzy system in differentiating between motion from nursing staff and patient care, and patient agitation. Hence, the short list of fuzzy inference system rules and membership functions developed is found to be effective in enabling this direct correlation between subjective and computer based assessment of the patient motion signal.

Fig. 9 presents the correlation between physiologically quantified agitation using four different physiological signals [11,19] and agitation quantified based on the motion sensing approach presented. Motion based agitation sensing is more directly correlated to the effective signals used in subjective nursing staff assessments of patient agitation [12,13] so their correlation is not surprising. However, the physiological measurements are based on the hypothesis that agitated motion and agitation itself are manifested in the autonomic nervous system responses seen in these physiolog-

![Fig. 7 Patient 2: patient (frame 1) and nurse (frame 2) correlation coefficients and resulting agitation index (frame 3) for a selected 30 min period. Nursing assessed agitation is shown over the agitation index using the Modified Riker Scale.](image-url)
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Fig. 8 Patient 3: patient (frame 1) and nurse (frame 2) correlation coefficients and resulting agitation index (frame 3) for a selected 30 min period. Nursing assessed agitation is shown over the agitation index using the Modified Riker Scale.

cal signals, which is a slightly different definition. These physiological signals also show good correlation. However, the combination of all of these metrics is seen to correlate equally well, if not better, than the patient movement metric alone, illustrating the potential for such a multi-signal approach.

Patients 1 and 3 show similar levels of nursing and patient motion in Figs. 6 and 8, whereas Patient 2 has greater nurse motion than patient motion in Fig. 7. However, in each case the fuzzy quantifier is selectively judging the contributions of each. One major confounding issue is that nursing staff may be more or less involved with the patient depending on the level of agitation so that high levels of agitation may see lower relative levels of nursing motion for safety reasons than lower levels. A second is that each nurse treats aggravated motion differently, which leads to different levels of nursing motion, relative to patient motion, for the same agitation level. The fuzzy logic rules have shown the basic capability of distinguishing nursing and patient motion for judging agitation, but will require further study to delineate the exact capability of this approach.

It is also worth noting that the results for patient motion in Figs. 6–9 are all non-smooth due to the frame-to-frame definitions of the correlation coefficient and agitation index values in Eqs. (4) and (5). The noisy look of these signals is distinctly pronounced for the low agitation levels seen in Fig. 6. Clinically, smoother responses would be more suitable as a feedback signal for controlling sedation administration. The data presented in these figures would be smoother if a higher frame rate or additional filtering for rms or moving average values were used. Finally, considering longer time period windows, rather than immediate frame-to-frame calculations would also smooth these results.

Finally, the proposed method is computationally very simple and adequately filters out unwanted noise and inputs. This simplicity ensures it can be readily implemented in real-time using a C/C++ or other similar PC software platform. Finally, it should be noted that this implementation was developed to prove the concept of measuring patient agitation using digital imaging and a fuzzy inference system, so the rules offer significant opportunity for further development and fine tuning with a
Fig. 9 Patient 3 results with a variety of agitation metrics and a combined score for a different time frame than shown in Fig. 8.

larger, more controlled clinical trial and test data base.

5. Conclusions

A method of physiologically quantifying patient agitation based on reliable, objective digital imaging based motion sensing is presented. The concept quantifies patient and nursing staff motions and uses a fuzzy inference system with simple rules to differentiate between motion due to patient care and manifestations of patient agitation to provide an objective, continuous measurement of agitation. The basic method splits the image into patient and nursing (edge) regions and determines a normalised measure of motion power in each. The method can also be extended to individually examine motion of specific body parts or areas of the patient. The system was developed using simulated patient agitation video data. Proof of concept clinical trials are performed using five ICU patients being weaned from sedation, with typical results from three patients presented, to prove the overall concept and system developed.

Results show that agitation can be assessed in sedated ICU patients and quantified using this approach, including differentiating periods of calm. Periods of detected agitation in ICU patients correlate well with subjective assessment by trained medical staff using the modified Riker SAS. These results show that agitation can be quantitatively measured and assessed using this computationally inexpensive digital imaging approach. Further results show the method correlates well with agitation assessed using physiological signals and that they can be combined into a final agitation metric with good correlation for the one subject tested. Clinically, this research presents a proof of concept system capable of providing real-time assessment of patient agitation where nursing staff are not always unbiased or available. These measurements have the potential to provide better understanding of patient agitation as well as being used to guide sedation administration and selection.

These results represent an initial proof of concept, particularly in regard to the values and rules used in the fuzzy inference system. Significant areas of future work include the development of additional quantification rules and methods for the fuzzy inference system, as well as further study of the correlation with agitation determined from measured biomedical signals. Most importantly, there is a need to test these systems on greater numbers of patients to obtain more robust, statistical correlation.

References


