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An Adaptive Approach to Decomposing Patient-Motion Tracking Data Acquired During Cardiac SPECT Imaging

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Abstract

Patient motion during cardiac SPECT imaging can cause diagnostic imaging artifacts. We have implemented a Neural Network (NN) approach to decompose monitored patient motion data, gathered during cardiac SPECT imaging, using the Polaris stereo-IR real-time motion-tracking system. Herein, we show the successful decomposition of Polaris motion data into rigid body motion (RBM) and respiratory motion (RM). The motivation for separating RM from RBM is that each is corrected using different methods. The NN requires the input of a RBM threshold sensitivity limit, as well as the median filter window width. A two step approach can be used in setting the median filter width. In the 1st NN run the median filter window width is initially set to a “fixed” width typical of the respiration period. This 1st NN run does an initial decomposition of the data into RM and RBM. The RM is then fed into an FFT algorithm to produce a respiratory period output file for use during a 2nd NN run, where the median filter width can “adapt” to the patient respiratory rate at each time point. Implementation of the NN was in the UNIX environment with Interactive Data Language (IDL). Decomposition of simulated “signals known exactly” RBM and RM resulted in average value errors less than 0.11 mm for RBM steps, and an overall root mean square error of only 0.3 mm for RM or RBM. Volunteer RBM and RM Polaris data were successfully decomposed by the NN with RBM steps resolved with an average difference of only 0.8 mm as compared to values displayed on the SPECT gantry console which are only to the nearest mm. A plot of the NN RM trace and the synchronized trace from a pneumatic bellows shows virtually identical characteristics. Anthropomorphic phantom RBM and RM were decomposed and used to correct motion in SPECT images during reconstruction. The motion corrected slices looked visually identical to slices acquired without motion, and comparison of slice count profiles further confirmed the correction.

I. Introduction

Patient-motion artifacts are a major cause of diagnostic image-quality degradation, especially in SPECT and PET where patients must remain still for protracted periods of time [1,2]. Patient motion always includes respiratory motion (RM), but may also include other body motion. Herein, we consider only rigid-body motion (RBM) for the latter. We have recently shown [3] that the Polaris stereo-infrared (IR) real-time motion tracking system can output a data trace which contains information on both these types of motion. Our system reports the three-dimensional (3-D) positions of small reflective spheres that are attached to bands around the patient’s abdomen and chest. Measurements with the Polaris system have a vendor-specified

0.35-mm accuracy and a 0.2-mm repeatability. However, the RM and RBM information is mixed together in the Polaris output trace. Thus, the goal of this investigation was to develop a method for separating this information since each component is corrected utilizing different methods, as will be explained later. An accurate method would allow for reliable patient-motion compensation within iterative reconstructions of SPECT cardiac-perfusion imaging data since individual RBM correction and RM correction would be applied before the iterations started. Knowing the individual components prevents the wrong compensation technique from being applied to the wrong motion type, hence more reliable compensation. Our hypothesis was that an algorithm based on a neural network (NN) could be used for this purpose. Such a NN algorithm could also be applied to decompose 3-D motion data obtained from a “Visual Tracking System” (VTS) we are developing [4,5], or from other 3-D tracking systems.

II. Methods

A. NN Decomposition of Motion Trace Data

We have mounted a Polaris unit on the wall behind the gantry of a Philips IRIX camera as shown in Fig. 1. Polaris views the reflective spheres on the chest and upper abdomen of a patient through the tunnel of the gantry. Fig. 2 shows a plot of the vertical data from one sphere acquired from a human volunteer by Polaris. With a single sphere, Polaris records data at approximately 30 samples/sec. The main trace components are cyclical RM, and translational RBM that was produced by incrementally stepping the patient bed height. Our objective is to separate these contributions.

As given by [6], “In its most general form, a neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented using electronic components or is simulated in software on a digital computer”. By one further definition [7], “a neural network is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes”. One disadvantage of classifiers based on standard NNs is that they often admit little intuitive physical interpretation. Physics-based NN classifiers, on the other hand, use embedded knowledge and analytic elements that do have physical interpretations. In addition, the physics-based NN classifiers can often outperform standard NNs [8]. We chose such a model for our application.

The design philosophy for the NN is to first estimate the RBM. We shall let the vector $\mathbf{p}(t)$ represent the 3-D Polaris data for time samples t in the interval $[0, T]$. The RBM estimate vector at time t is $\mathbf{R}(t)$. The RM estimate $\mathbf{B}(t)$ is then the difference $\mathbf{p}(t) - \mathbf{R}(t)$. A flowchart of the NN logic to estimate $\mathbf{R}(t)$ from $\mathbf{p}(t)$ is shown in Fig. 3. We show a flowchart rather than a typical NN nodal representation since we feel it demonstrates the methodology more clearly. The unsupervised adaptive physics-based NN connection strengths were determined and assigned based on prior experiments. The determination of $\mathbf{R}$ begins with a smoothing module that applies median filtering and thresholding to yield an intermediate estimate $\mathbf{s}(t)$ that has most of the RM removed. To get $\mathbf{s}$, the three coordinate traces of $\mathbf{p}$ are separately smoothed using a sliding median filter with a window width of w . Ideally, w would equal one respiratory period (typically 4 to 6 seconds [9]) in order to average out the cyclical RM signal in the data. The filter output $\mathbf{p}'(t)$ is then subjected to a thresholding operation that preserves gross motions exceeding a pre-set threshold d . This is done at a given time t by comparing the “present” position $\mathbf{p}'(t)$ and the “forward” position $\mathbf{p}'(t+w)$. If the difference in these positions exceeds d , $\mathbf{s}(t)$ is set to whichever position is closest to $\mathbf{p}(t)$. Otherwise, $\mathbf{s}(t)$ is taken to be the average of the positions. The step threshold d should serve as the minimum size RBM change of interest (i.e. 1 mm etc.). The second stage for obtaining $\mathbf{R}(t)$ is the RBM module (Fig. 3), wherein the sliding median filter is applied to $\mathbf{s}(t)$ to give $\mathbf{s}'(t)$. A check for persistent RBM is then made.

For a given t , if the Euclidian distance from the current position $\mathbf{s}'(t)$ to the forward position $\mathbf{s}'(t+w)$ and to the “gapped” position $\mathbf{s}'(t+2w)$ both exceed d , then a step motion is assumed to have occurred and $\mathbf{R}(t)$ becomes the average of the previous RBM point $\mathbf{R}(t-1)$ and $\mathbf{s}'(t+w)$. However, if the motion is not persistent, then $\mathbf{R}(t)$ depends on when the last step occurred. If a step occurred at time $t-1$, $\mathbf{R}(t)$ is set to $\mathbf{R}(t-1)$. Otherwise, $\mathbf{R}(t)$ is assigned the value $\mathbf{s}'(t+w)$.

Of course, proper selection of parameters d and w is important for good NN performance. If d is set much smaller than magnitudes of RBM that are of interest for motion correction, then the NN will mistakenly classify most of the motion as RBM. With thresholds set too high, the NN will be desensitized to RBM occurrences that may be of interest. Similarly, setting the filter window width w much smaller than a typical respiration period risks having the NN classify most of the motion as RBM.

Variations in the patient’s breathing cycles are another issue in setting w . In discussing the NN flowchart, we suggested a fixed width could be determined as the mean of a patient’s respiratory period. We refer to this as fixed-mode operation of the NN. An adaptive mode is enabled by adjusting w based on the respiration period at a given time t .

To get the required estimates of $w(t)$ for the adaptive mode, we process the RM estimate $\mathbf{B}(t)$ from a fixed-mode NN run with a windowed-FT (Fourier Transform) algorithm [10] in order to analyze localized portions of the RM signal trace. A Gaussian window with a 2-second standard deviation was utilized. For each time t , we set $w(t)$ to be the period of the frequency with the maximum magnitude. However, the presence of residual RBM in $\mathbf{B}(t)$ can lead to spurious values of $w(t)$. One way of counteracting this, is to preprocess $\mathbf{B}(t)$ with a high-pass filter. We have also experimented with setting upper and lower limits for valid respiration frequencies

B. NN Operation with simulated motion

We tested the NN with a simulated “signal known exactly” (SKE) data set that mimicked clinical Polaris acquisitions. The intent was to investigate the effects of the NN parameters w and d . Fig. 4. shows the lateral (x-axis) trace component; the components for the vertical (y-axis) and axial (z-axis) were identical. This lateral trace consists of 700 samples centered at each of 4 different positions (1.0, 4.0, 2.0 and 1.0 mm, respectively) to simulate RBM. Note that since these same step position changes were also modeled in the y and z directions, the overall RBM magnitudes were $\sqrt{3}$ times these heights. Combined with the RBM was a sinusoidal RM with cycle periods of 77, 130, 35, and 77 samples having amplitudes of 1.0, 1.5, 2.5, and 1.1 mm, respectively. Again, the overall RM magnitudes were greater by a factor of $\sqrt{3}$. This is important to realize because the NN classifies RBM by comparing the step-threshold value d against the magnitude of the 3-D movement. Therefore, individual RBM changes in x, y, or z may appear that are less than d .

In this experiment, the NN was run with a variety of fixed median-filter window widths while using a constant threshold d . Widths from 30–400 data samples were tested in order to investigate the effect of mismatches between the filter width and the known respiratory period. We also tested RBM thresholds from essentially 0, up to 5 mm in 0.5 mm increments while maintaining a constant median filter window width to observe NN effects. The root mean square error (rmse) between the known RM and the NN-estimated RM was used to evaluate the effects of these different parameters. Note that the rmse errors for RM and RBM are identical because our algorithm enforces the relation $\mathbf{RM}(\text{true}) + \mathbf{RBM}(\text{true}) = \mathbf{B}(t) + \mathbf{R}(t)$ between the actual motion (left-hand side) and the sum of the NN estimates (right-hand side) at each data point. Thus, it follows that $\|\mathbf{RM}(\text{true}) - \mathbf{B}(t)\| = \|\mathbf{RBM}(\text{true}) - \mathbf{R}(t)\|$.

We also applied the windowed-FT to the estimated RM in order to gauge the accuracy of the recovered respiratory periods.

A second test with simulated data used the same sinusoidal RM, with the RBM applied as a ramp as illustrated in Fig. 5. The slope of the ramp was -0.00357 mm/scan providing -10 mm of motion over the 2800 sample points. The motivation behind use of the ramp RBM was to determine how the NN functions with gradual changes in RBM. Thus the NN operation will be tested with both a ramp and step simulated RBM to see how well it functions with both rapid and gradual changes.

C. Comparison of NN-Estimated RM to RM Determined by Respiratory Bellows in a Volunteer

We used a comparison between RM as measured via a respiratory bellows [9] to that determined by the NN to test the ability of the NN to separate RM from RBM in a human volunteer. The volunteer was positioned on the bed of the SPECT system with the bellows and an elastic band with the IR reflecting spheres wrapped about their torso.

To synchronize the acquisition of the bellows and Polaris data on two different computers the volunteer was requested to take a deep breath shortly after the start of acquisition. Additionally the imaging bed upon which the volunteer was lying was moved vertically a known amount 3 times during the course of data collection to simulate known RBM. The Polaris tracking data shows RBM steps as well as the respiratory RM trace since it is a combined signal. The NN was run on the combined data to separate the respiratory motion (RM) from the rigid body motion (RBM) using a fixed median filter window width of 77, using the same rationale as explained above but with a data determined shorter average period due to the faster respiration rate of the volunteer in this experiment.

D. NN Test of Separation of RBM and RM in a Volunteer

A second experiment further tested the ability of the NN to decompose a volunteer's combined signal into the component RBM and RM in both "fixed" and "variable" window width modes. The 1st NN run was done with a "fixed" window width set to a pre-determined raw data average respiration period as calculated from the Polaris trace. The RM trace output was also processed by our FFT algorithm to produce the respiration period output file for use as input to the NN during a 2nd NN run to be done in "variable" adaptive mode. The effect that adaptive median window size changes have on RBM and RM output data was investigated.

E. NN-Derived RBM and RM Correction in Reconstruction

To test the ability of the NN derived estimates of RM and RBM to correct motion we used acquisitions of the Data Spectrum anthropomorphic phantom. Tc-99m radioactivity of equal concentration was added to the heart and liver compartments of the phantom. The phantom rested on a board placed on the IRIX bed. A periodic RM of approximately 2-cm amplitude was simulated by continuously sliding the board. Incremental RBM steps of -2 cm followed by $+4$ cm were also simulated, see Fig. 6. All motions were done in the IRIX axial direction (Z axis). The phantom was imaged while undergoing the performed motions, while the Polaris unit simultaneously monitored IR reflective markers mounted on an elastic belt attached to the phantom. The acquired motion data were mapped into IRIX co-ordinates [5] for use during reconstruction motion compensation. The rigid body motion steps and respiratory motion were decomposed by the NN, which then provided two output files to be used for image motion correction during reconstruction. The NN was operated with a fixed median window width for this experiment.

To enable motion correction, a SPECT list-mode acquisition was acquired in synchrony with Polaris recording of the 3-D locations of IR reflective spheres on the elastic band wrapped

about the phantom. The motion of the spheres was then separated into RM and RBM using our NN.

With parallel collimators, a 3D translation of the body results in a projected 2D translation in the detector plane. Compensation for RBM is achieved by moving the events in the list-mode file in the direction opposite to the 2D vector of RBM as a function of gantry angle.

With RBM of each event thus corrected, the list-mode file is then rebinned into 100-ms projections and RM is corrected according to our previously reported methods [9,11]. This method divides the RM signal into 8 respiratory states. The 100-ms projections acquired at the same angle and at the same respiratory state are summed together, so that one projection per state and per angle is obtained. RM compensation is obtained by finding the center of mass (COM) of the projections and shifting the projections so that the COM is aligned. The projections acquired at the same angle are then summed together to obtain one projection per angle. The images were reconstructed with attenuation compensation using the OSEM algorithm with 8 projections per subset and 8 iterations. A visual and count profile comparison is then made to slices reconstructed from a data set acquired when the phantom was stationary.

III. Results and Discussion

A. NN Operation with simulated motion

Fig. 7 shows the root mean square error (rmse) results comparing the known values to the NN decomposed values, utilizing different initial median window width choices from 30 to 400 with a constant 1 mm threshold. Note that the overall rmse is a minimum at a width of 150 samples at about 0.3 mm error (upper trace). Since all 4 RM periods and RBM steps are included in this combined error calculation, a closer inspection of the error for only the 130 period component shows a smaller RBM or RM rmse error of only about 0.11 mm at the 150 NN window period, with the other periods of 77 and 35 about 0.16 mm or less. The conclusion is therefore to set the 1st NN run fixed window width equal to or slightly larger than the longest respiration period expected. The Fig. 7 rmse error shows a significant increase if the shortest respiration period window widths of only 30 to 40 are utilized and should not be used since the overall rmse errors reach 0.82 or 0.71 respectively. Otherwise the setting of the 1st NN run window width appears to have some latitude when set to larger widths, since the primary goal is to maintain respiratory trace integrity for FFT processing.

The rmse result using different RBM detection thresholds was also determined with multiple NN runs while keeping a constant fixed median filter width of 150. The plot of the data is shown in Fig. 8. The results showed that for our test case body positions of 1, 4, 2, and 1 mm, representing RBM step changes of 3, 2, and 1 mm, that the selection of a 1 mm threshold detected all step changes with the smallest overall rmse of only 0.303 mm. Thresholds lower than 1 mm classify more of the signal as RBM (rmse 0.340 mm), and up to 2 mm slightly less of the signal as RBM (rmse 0.377 mm) being higher in rmse in either case, but performing similarly. However, if the threshold is set higher than 2 mm, the rmse will increase more rapidly. The rmse errors for the 4 individual respiratory periods are also shown and reflect their respective threshold desensitization effects. Typically, a threshold setting of a SPECT pixel width would allow a user to detect and correct for equivalent sized patient motions.

Fig. 9 shows the 1st NN run decomposed RBM trace of the data of Fig. 4 using a fixed median filter width of 150 and threshold of 1 mm. The result is errors of less than 0.114 mm when comparing the average NN step values of 0.921, 3.886, 2.041, and 0.887 to the simulated RBM. The 1 mm threshold was chosen to allow detection of simulated steps of magnitude significantly less than the 4.2 to 6.3 mm pixel widths typically employed in SPECT acquisition. A slight smoothing of the transition between the different stages of RBM is noted in Fig. 9.

Note however that the smoothing is small compared to the smallest step in location which was 1 mm. Therefore, this smoothing is likely to have little impact on correcting SPECT studies where the system FWHM is greater than 1 cm.

Fig. 10 shows the RM estimated by the NN calculated as the difference between the input signal (Fig. 4) and the estimated RBM (Fig. 9). At 30 samples per second the known values for the periods correspond to 2.567, 4.333, 1.167, and 2.567 seconds, respectively. The average values for the periods obtained from Fig. 10 using the FFT algorithm to estimate them were 2.576, 4.336, 1.167, 2.576 seconds respectively which shows an excellent agreement between known and FFT determined periods. A 2nd NN run in the adaptive mode was performed but is not shown here due to space limitations. The results did not show any significant difference from the optimal rmse fixed 150 window width run, which is reasonable considering the consistent nature of the 4 known respiratory period RM signals applied.

Fig. 11 shows a NN run decomposed RBM trace of the ramp RBM plus RM data of Fig. 5 using a fixed median filter width of 150 and threshold of 1 mm. The simulated continuous ramp is reproduced as a series of small steps.

Multiple scans are required before the ramp of slope of -10 mm over 2800 scans will reach the selected threshold limit (e.g. 1 mm), and then a step will appear. This threshold can be set to less than 1 mm and the ideal ramp function would be approached at the expense of passing noise through as RBM. As expected, the initial and final scans being decomposed by the NN have incomplete knowledge, thus we see the 1 mm step on the ends. The balance of the scans show less than the 1 mm threshold since more knowledge was available for the NN to classify the motion as being RBM.

Fig. 12 shows the RM estimated by the NN calculated as the difference between the input signal (Fig. 5) and the estimated RBM (Fig. 11). It can be seen that the amplitudes and periods of the simulated RM signals are successfully decomposed, and the minor variations are due to the RBM detection threshold setting and RM being calculated as the difference.

B. Comparison of NN-Estimated RM to RM Determined by Respiratory Bellows in a Volunteer

Fig. 13 shows Polaris and bellows data for a volunteer lying on the imaging table of the SPECT system. Notice that the Polaris signal shows both the RBM steps and RM, but solely RM is observed with bellows. The NN was run with a 77 sample wide fixed median filter and a 1 mm threshold to decompose the Polaris data. The fixed window width of 77 was selected on the basis of being the average RM period observed in the reported Polaris data.

The NN derived steps in imaging table position from the Polaris data were 15.2, 17.6 and 21.0 mm. These compare very well to the IRIX steps of 16, 20, and 22 mm determined from the displayed bed heights. The average difference between the Polaris NN derived and IRIX displayed steps was only 1.4 mm which is very good since the IRIX displayed bed positions are only to the nearest 1 mm. Note the excellent agreement between the NN derived RM data, shown plotted versus the bellows data in Fig. 14. There is excellent correlation and phasing with only minor nuances at the step change locations.

C. Test of Separation of RBM and RM in a Volunteer

Fig. 15 shows the NN's ability to decompose volunteer RBM and RM using a "fixed" median filter width of 77 during the 1st NN run. The decomposed RM data output file was fed into the FFT algorithm and predominantly showed a 2.5 sec. respiratory period indicating the volunteer was breathing faster than normal. The FFT "respiratory period" output file was used by the NN in a second run in "variable" or adaptive mode. The intent of the second pass is to determine RBM more robustly for varying patient respiratory rates during SPECT imaging. The resulting

output files of the 2nd NN “adaptive” run are shown in Fig. 16 and are similar to the “fixed” median filter run of the 1st NN shown in Fig. 15. Note the average value steps in Fig. 16a of 1.5, 2.7, 1.96, 4.75, 2.02 and 14.82 mm falloff compared to the SPECT gantry console (1 mm resolution) display values of 2, 2, 3, 4, 2 and 13 mm results in an average absolute difference error of only 0.8 mm.

D. NN-Derived RBM and RM Correction in Reconstruction

Fig. 17a shows the recorded axial signal from the Polaris for the manually simulated RBM and RM of the anthropomorphic phantom on the imaging table of the SPECT system. The NN run with a “fixed” 146 sample median filter window width and a 1.166 mm threshold resulted in the RBM estimate shown in Fig. 17b and RM shown in Fig. 17c. Note that the total time period shown in Fig. 17 is 12.8 minutes. The RBM and RM outputs were utilized to correct for motion during SPECT reconstruction. Since the respiratory rate period was held relatively constant as a result of our simulated controlled respiratory motion, the “fixed” window width run was felt the best to demonstrate the image reconstruction improvements as a result of compensation for RBM and RM at this time. Fig. 17 clearly shows the RM simulation of approximately ± 1 cm amplitude as manually simulated axially, with additional RBM axial position changes from approximately -70 mm to -90 mm, then from -90 mm to -50 mm (i.e. the steps of -2 and $+4$ cm simulated manually). The vertical and lateral axis data was also processed properly and showed minor motion, but plots are not shown due to space limitations.

The images shown in Fig. 18 are short axis slices of the anthropomorphic phantom. Note visually the heart wall and liver separation improvement from (a) no correction to (b) RBM correction only, with further improvement to (c) combined RBM and RM correction. Fig. 18d shows a slice from an acquisition in which the phantom was not moved and thus illustrates the gold standard for motion correction. Observe how the slice with RBM and RM corrections looks virtually identical to that in which motion was not simulated during SPECT acquisition. Fig. 18e shows a radioactive-decay corrected count profile across the indicated plane in (a) through (d). Note the significant improvement that correcting for RBM and RM can provide. That is, the profile from the slice with correction is very nearly back to the no motion profile, with heart wall and liver very distinctly shown. Fig. 19 shows polar maps from the short axis reconstructions. These too show significant improvement from the no correction (left most), to the RBM correction only, to combined RBM and RM correction, which ultimately looks very similar to the no motion gold standard (far right).

E. Limitations, challenges and future directions

One important aspect of NN operation is the timing and appearance of RBM steps in plots in relation to actual data movement. In most cases the phase is very closely aligned when appropriate filter widths and thresholds are utilized. Even if the phasing of RBM is off by perhaps 15 samples at 30 samples per second, this represents only 0.5 seconds worth of counts in a typical SPECT acquisition of 20 seconds or more per projection and thus would not be significant. Extremes in selecting window widths or thresholds will possibly create RBM steps based on data farther removed in relation to the current time point and phase shifts can become larger. These shifts of even 1–2 seconds still only represent a small portion of time and counts. Thus RBM phasing issues do not seem to be a major issue affecting NN decomposition performance.

Future work is planned to develop an error expression that compares the output RBM of the NN to an integrated combined Polaris raw data trace, and then to develop an iterative method of improving the fit by minimizing the error by dynamically tuning NN parameters. We also plan to evaluate adjustment of the three NN median filter weightings to further improve algorithm performance.

Currently, our NN models RBM motion by making step changes if the chosen threshold is exceeded. This RBM works well for image correction use, but as small thresholds are set a staircase effect can be seen in estimated RBM motion. Future work will involve evaluating other types of NN RBM change curve fitting such as linear.

Our windowed FFT algorithm processes the 1st NN run RM. It sometimes sees artifactual low-pass motion (i.e. step level changes) frequencies as predominant energy. Thus we had to apply boundary limits for realistic respiratory period determination. We will evaluate the potential of algorithmically determining the number of data acquisition cycles in a respiratory cycle through signal processing techniques. This would create the temporal respiratory periods for the median filter window widths based on the raw data itself, avoiding the FFT processing step, thus requiring only one NN run.

A future challenge will be estimating combined RBM from multiple markers. Clinically we plan to use 2 elastic belts with 3 to 4 markers each. If all markers show the same RBM in 3D we would assume translation; however, if they are not the same they would involve a rotation component which will need to be determined. Since the belt stretch will be a non-RBM component of motion present, we will have to develop ways of determining the “best” fit RBM to the RBM output of the individual markers.

IV. Conclusions

The NN algorithm has successfully decomposed RBM and RM for volunteer and anthropomorphic phantom experiments as well as for simulated signal known exactly (SKE) studies. Future work will include use of the NN to decompose other 3-D tracking data as from an optical visual tracking system (VTS) we are developing.

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V. References

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Fig. 1. The acquisition set-up utilizing Polaris and the Philips IRIX SPECT camera. The Polaris system is mounted on the right-hand wall. The bright white spots on the patient's torso are IR-reflecting spheres attached to two elastic belts, which can be monitored from 0.48 to 2.4 m axially.

Fig. 2.

A typical Polaris data trace using a single reflective sphere. This trace indicates the patient's vertical motion. Polaris generates similar traces for the lateral and axial axes.

Fig. 3. NN flow-chart logic as applied to the Polaris data for 1 marker.

Fig. 4. Simulated signal as applied to the X axis (Y and Z axis are identical) showing simulated respiratory motion (RM) sinusoid and rigid body motion (RBM) steps.

Fig. 5. Simulated signal as applied to the X axis (Y and Z axis are identical) showing simulated respiratory motion (RM) sinusoid and rigid body motion (RBM) as a ramp of -10 mm over 2800 scans.

Fig. 6.

Plot of Polaris reported data showing simulated Z axis (axial) motion as applied to the anthropomorphic phantom by sliding the board. This forms the input data to the NN for decomposition into RBM and RM.

Fig. 7.

Varied median filter width root mean square error (rmse) comparison of the fixed median filter window width NN run decomposed respiration trace data to the signal known exactly (SKE) respiration periods and amplitudes applied for overall signal, and individual signal from each of the 4 different respiratory rates. The rmse shown for RM is the same for RBM.

Fig. 8.

Varied threshold root mean square error (rmse) comparison of the fixed median filter window width NN run decomposed respiration trace data to the signal known exactly (SKE) respiration periods and amplitudes applied for overall signal, and individual signal from each of the 4 different respiratory rates. The rmse shown for RM is the same for RBM.

Fig. 9. Shows the NN Decomposed X axis rigid body motion (RBM) (Y and Z axis are identical) and the known applied RBM simulated steps of 1, 4, 2, and 1 mm. The NN run was done using a fixed Median Filter window width of 150 data samples, and a detection threshold of 1 mm., using 'XYZ' Euclidian distance as the threshold measure for comparison.

Fig. 10.

The step test NN decomposed X axis respiratory motion (Y and Z axis are identical) showing the simulated respiratory periods of 77, 130, 35, and 77 data samples, with amplitudes of ± 1 , ± 1.5 , ± 2.5 , and ± 1.1 mm respectively. The NN run was done using a fixed Median Filter window width of 150 data samples, and a detection threshold of 1 mm.

Fig. 11.

Shows the NN Decomposed X axis rigid body motion (RBM) (Y and Z axis are identical) for the ramp input over the 2800 scans. The NN run was done using a fixed Median Filter window width of 150 data samples, and a detection threshold of 1 mm., using 'XYZ' Euclidian distance as the threshold measure for comparison.

Fig. 12.

The ramp test NN decomposed X axis respiratory motion (Y and Z axis are identical) showing the simulated respiratory periods of 77, 130, 35, and 77 data samples, with amplitudes of ± 1 , ± 1.5 , ± 2.5 , and ± 1.1 mm respectively. The NN run was done using a fixed Median Filter window width of 150 data samples, and a detection threshold of 1 mm.

Fig. 13.

Trace showing bellows signal proportional to respiratory volume and Polaris signal for changes in vertical location of a marker mounted on a band wrapped around the torso of a volunteer. Note the “in phase” nature of the traces and that the Polaris signal varies with RBM as well as RM.

Fig. 14.

Trace showing NN derived RM from Polaris signal shown in Fig. 15, plotted against the RM signal from the bellows.

Fig. 15.

The 1st NN run decomposition of volunteer data, X axis, (Y, Z axes not shown but perform similarly), a) RAW & RBM, b) RM, done with “fixed” median filter window width of 77 samples. (~2.5 sec period, 30 s/s).

Fig. 16.

The adaptive 2nd NN run of volunteer data, X axis, (Y, Z axes not shown but perform similarly), a) RAW & RBM, b) RM, done with FFT determined median filter window width periods.

Fig. 17.

NN Decomposition Run of 23000 data acquisition samples with a fixed median window width of 146 samples and detection threshold set to 1.166 mm using an Anthropomorphic Phantom showing simulated RBM and RM. Shown are the IRIX Z axis position values, a) RAW data (with RBM overlay), b) RBM only, and c) RM only.

Fig. 18.

Short axis slice through heart and liver of anthropomorphic phantom a) No corrections, b) RBM correction only no RM correction, c) RBM and RM correction (i.e. fully corrected), d) Slice from phantom acquired with no motion, e) Count profiles across indicated area corrected for decay of counts for RB and RBM.

Fig. 19.
Polar Maps of Short Axis Reconstruction; a) NO corrections, b) Rigid Body correction only,
c) Rigid and Respiratory corrections, d) No Motion Gold Standard.