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(54) **SYSTEM AND METHOD FOR PREDICTING TIRE FORCES USING TIRE DEFORMATION SENSORS**

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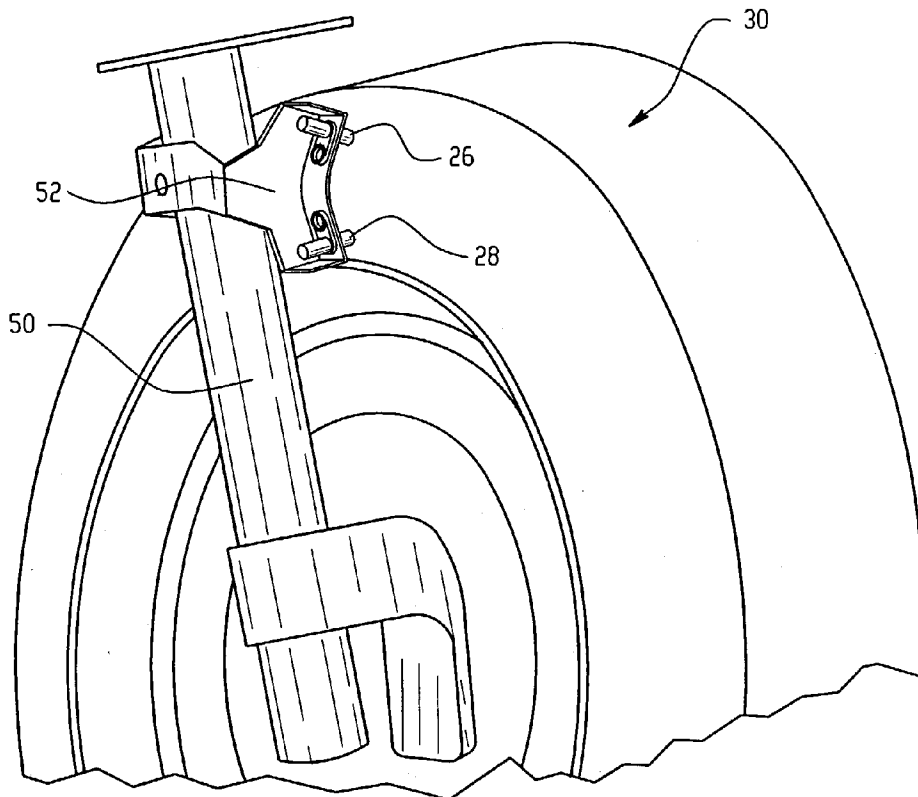
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(63) Continuation of application No. 09/584,230, filed on May 31, 2000, now Pat. No. 6,550,320.

(57) **ABSTRACT**

A system and method for predicting the forces generated in the tire contact patch from measurements of tire deformations, including separating the lateral force, the vertical force, and the circumferential torque using measurements of tire deformations. A system and method for using a trained neural network or bilinear equations to determine any combination or permutation of one or more of any of the following from tire sidewall deformation sensors, e.g., magnetic tire sidewall torsion measuring (SWT) sensors: the lateral force acting on the tire, the circumferential torque acting on the tire, the longitudinal force acting on the tire, the vertical force acting on the tire, and forces and/or torques having any one or more of the foregoing as components thereof.



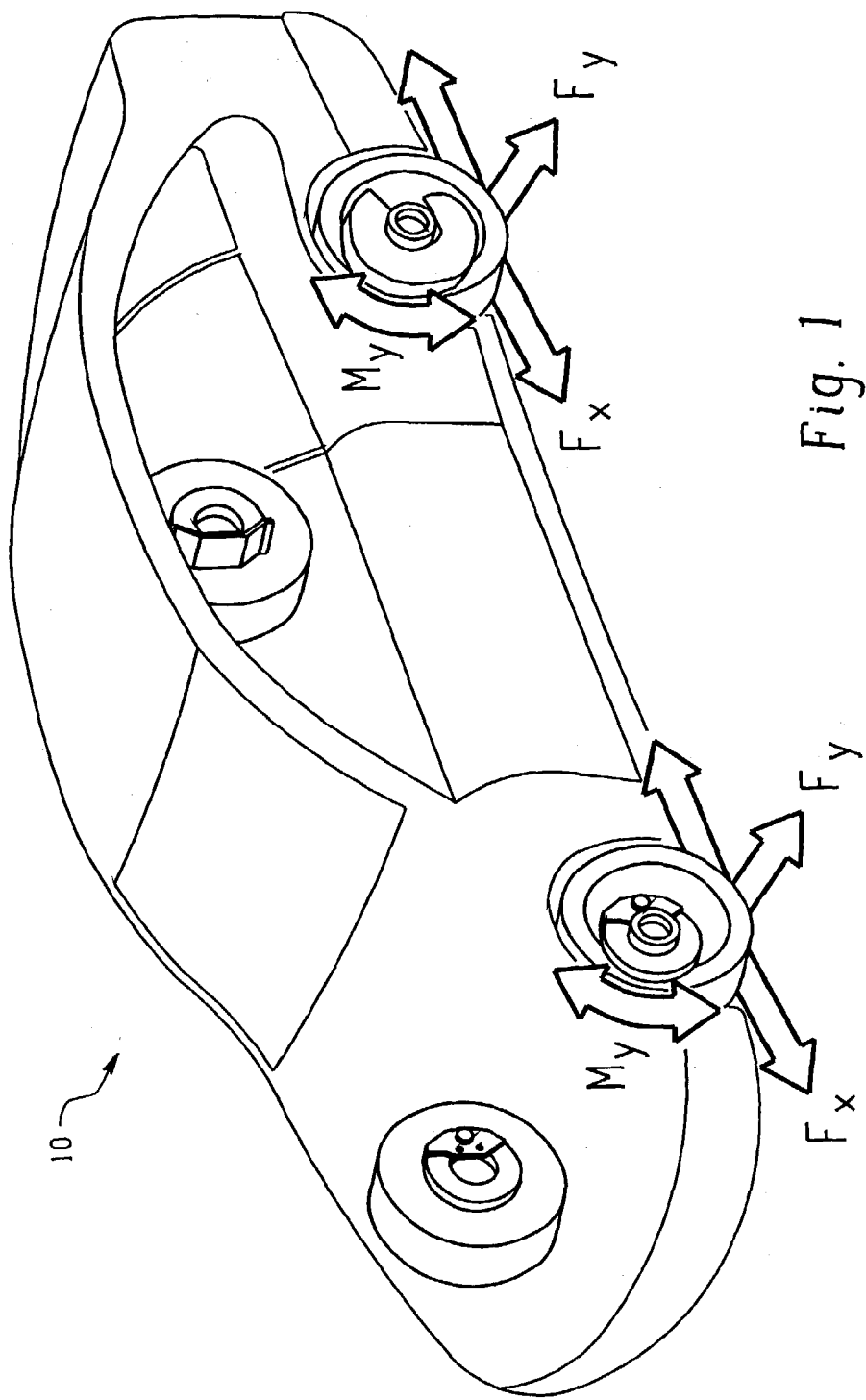


Fig. 1

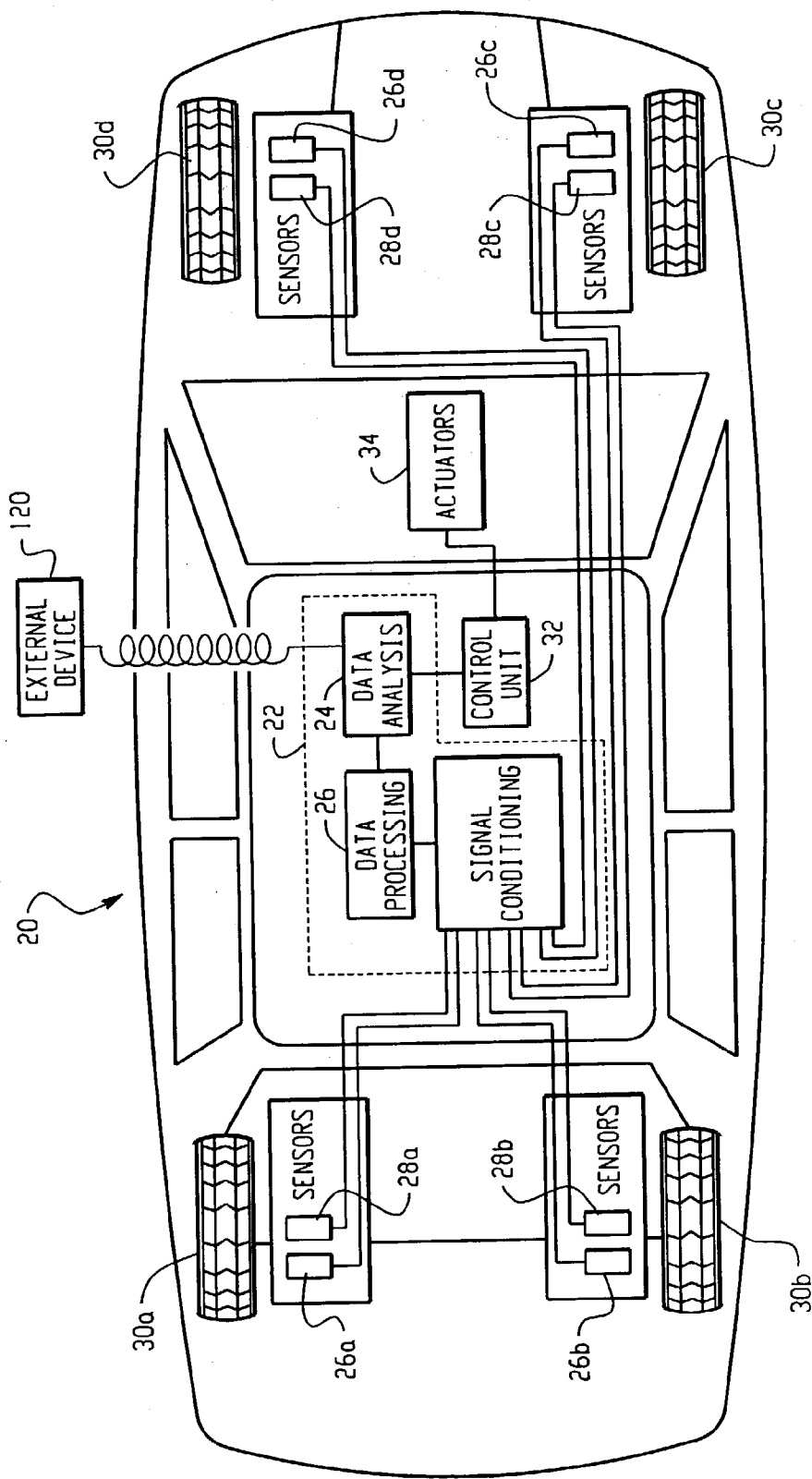


Fig. 2

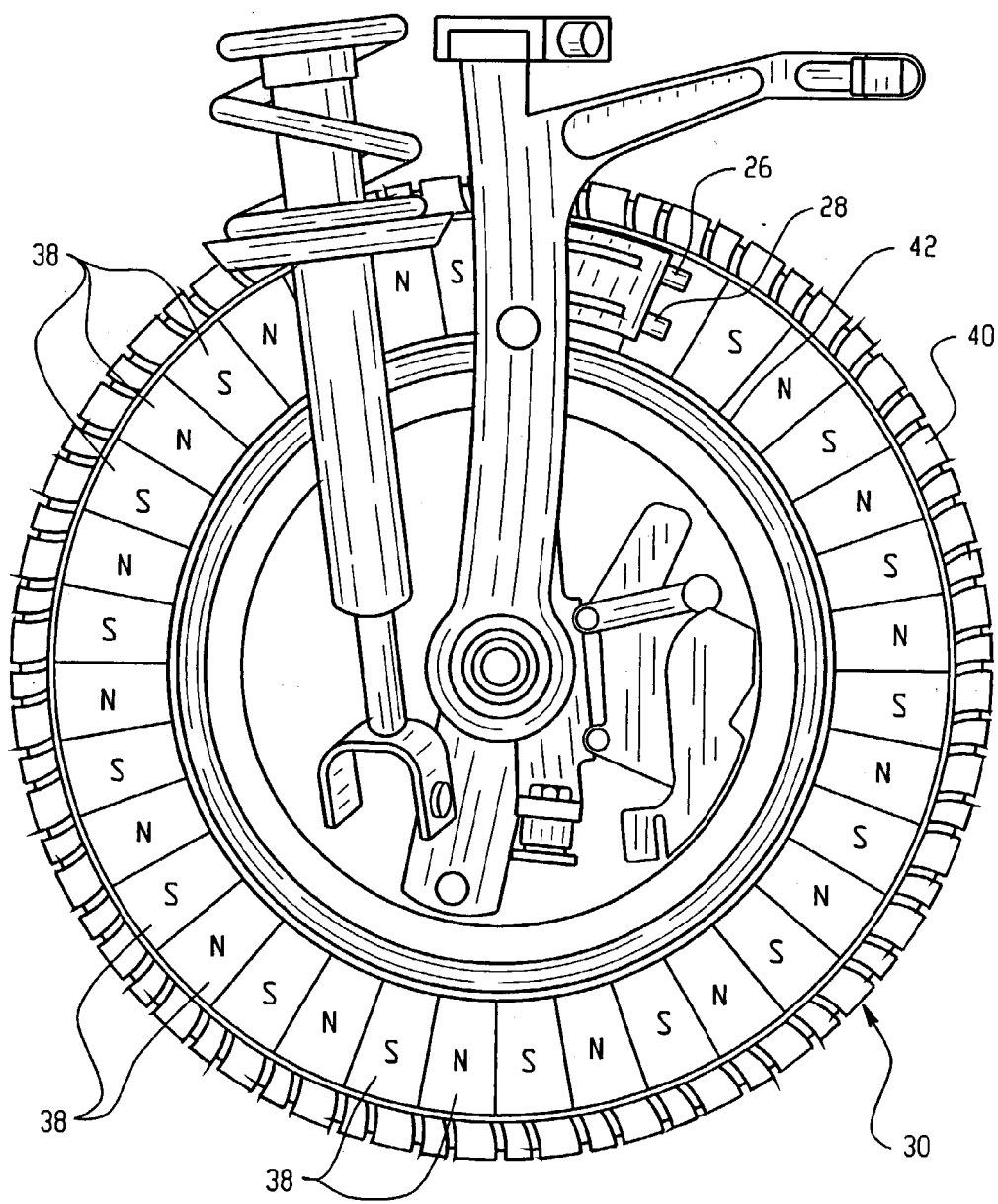


Fig. 3

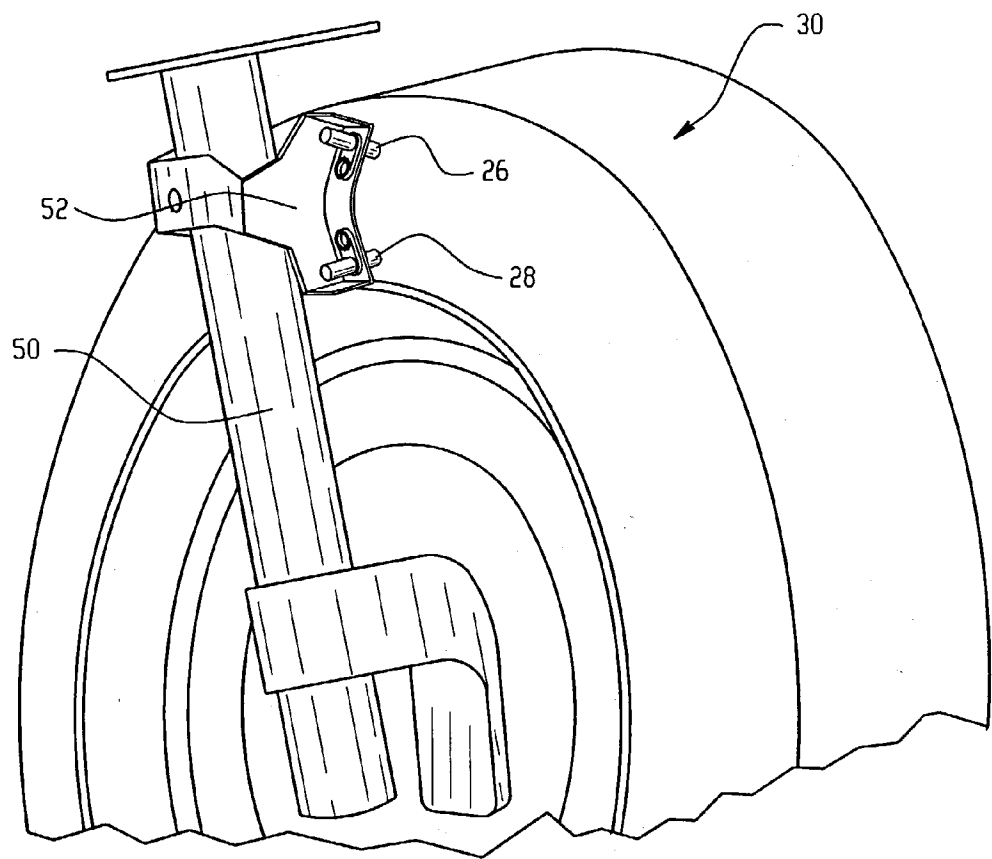


Fig. 4

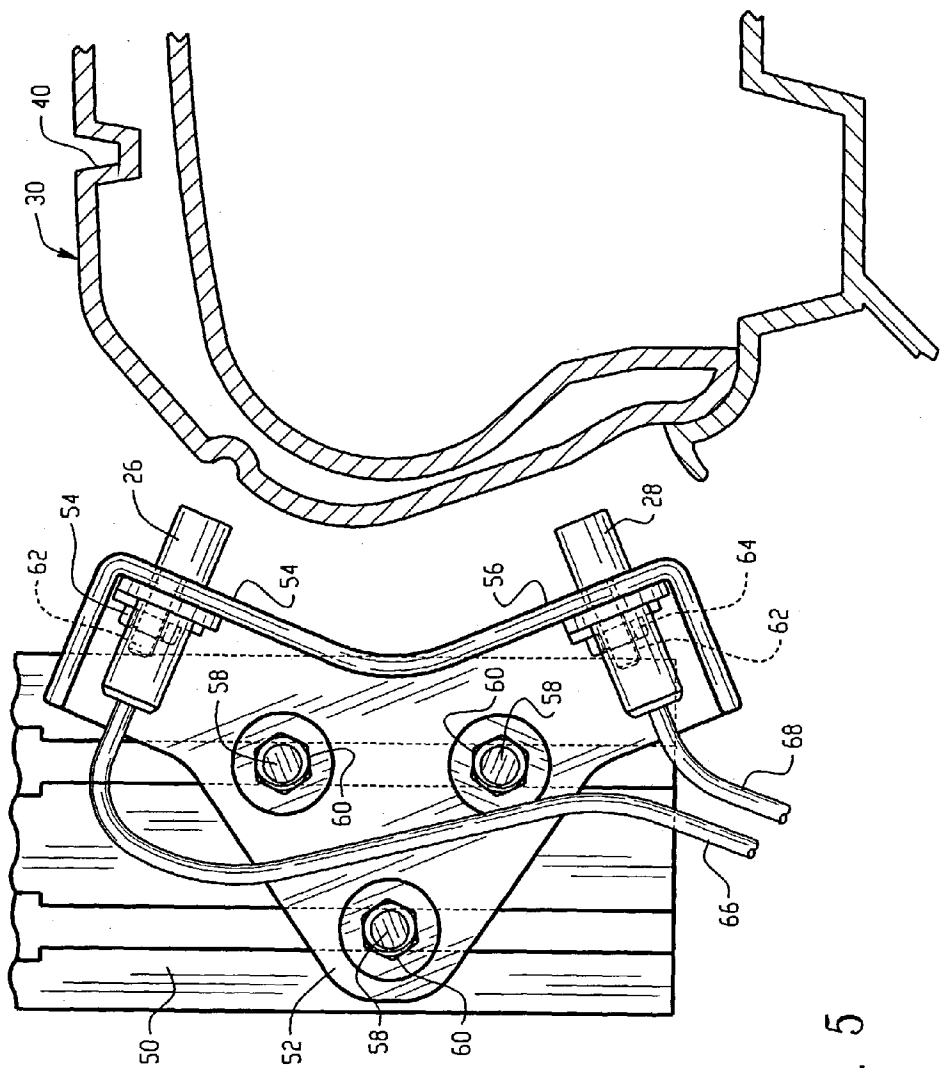


Fig. 5

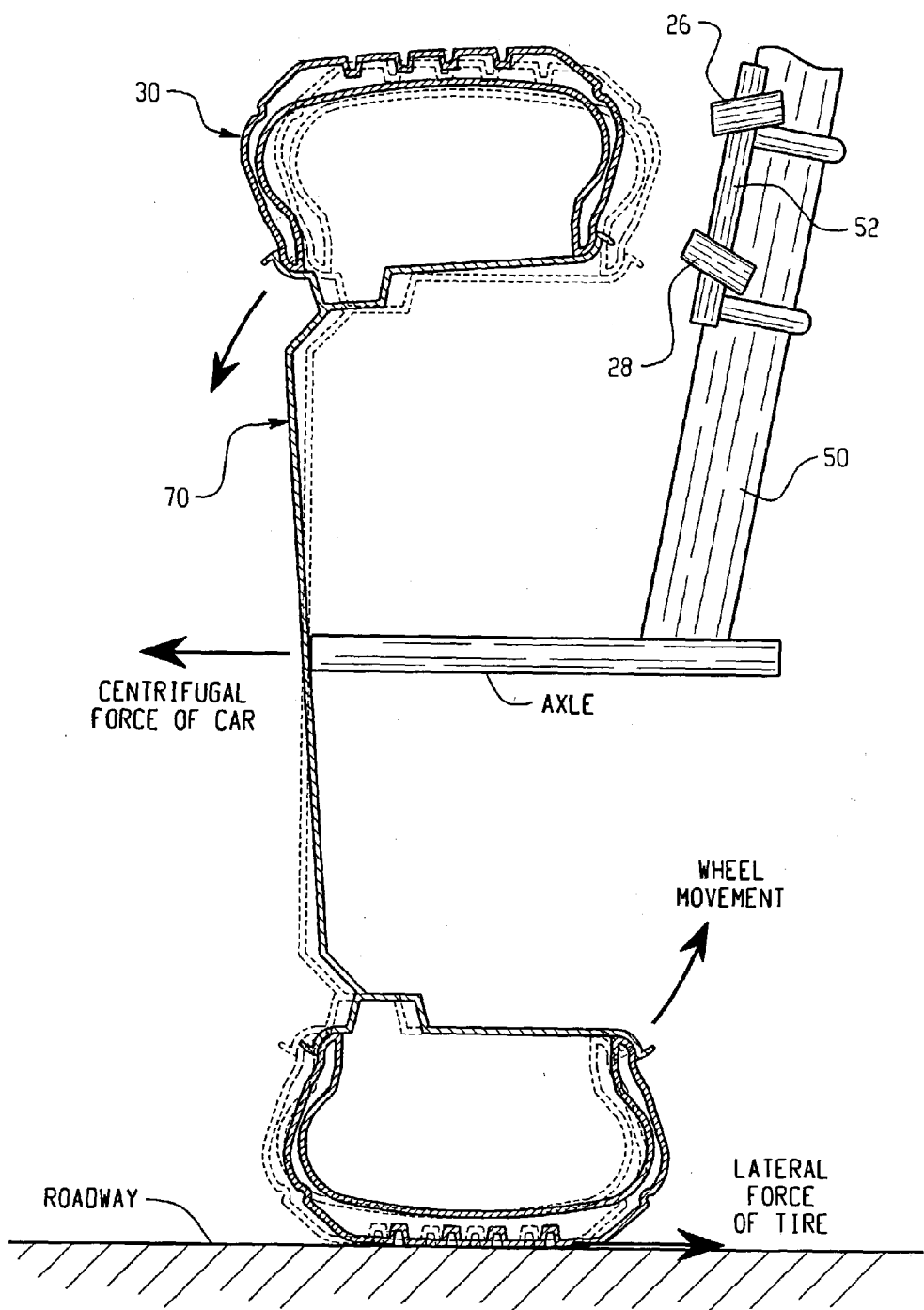


Fig. 6

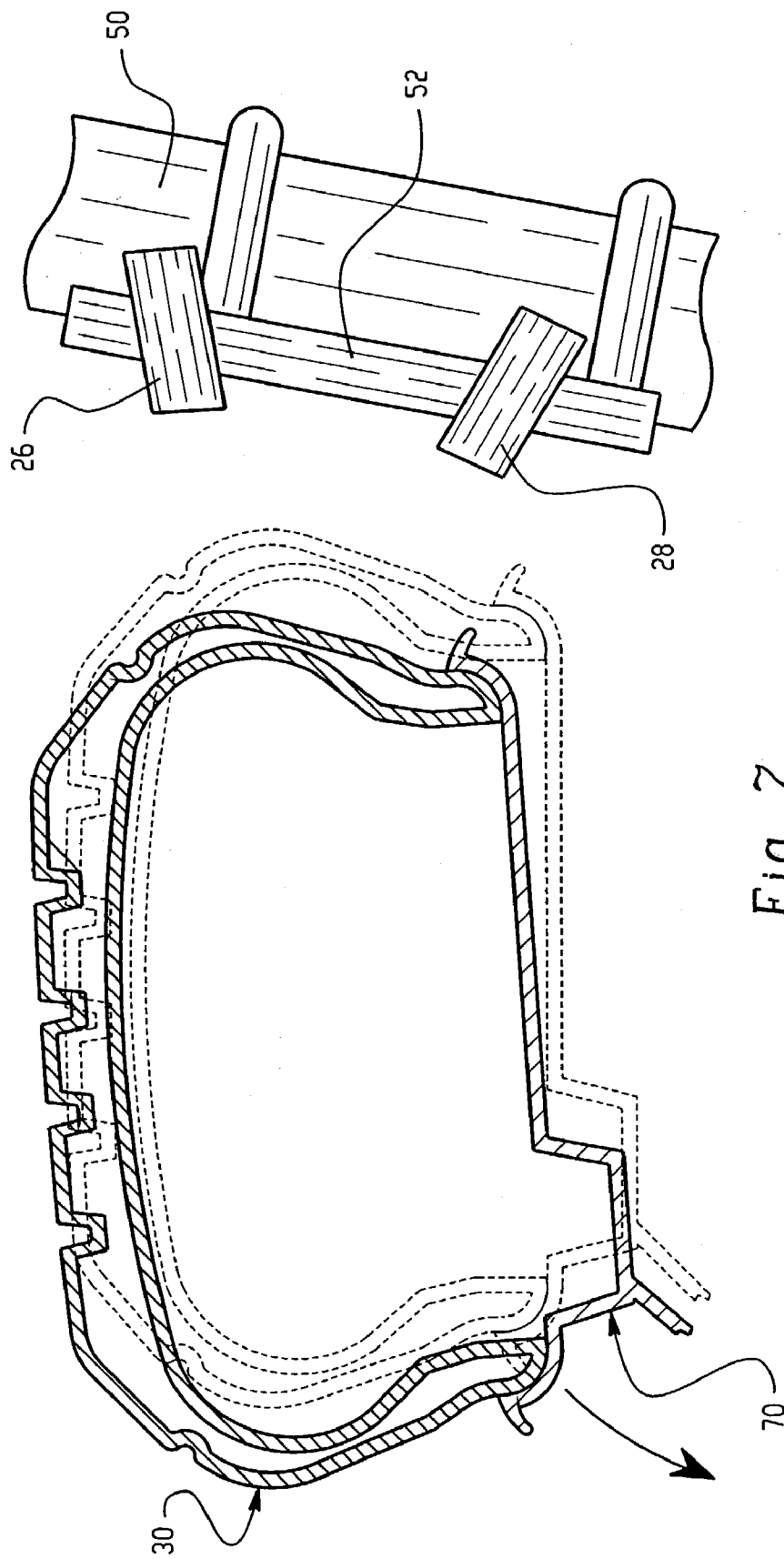


Fig. 7

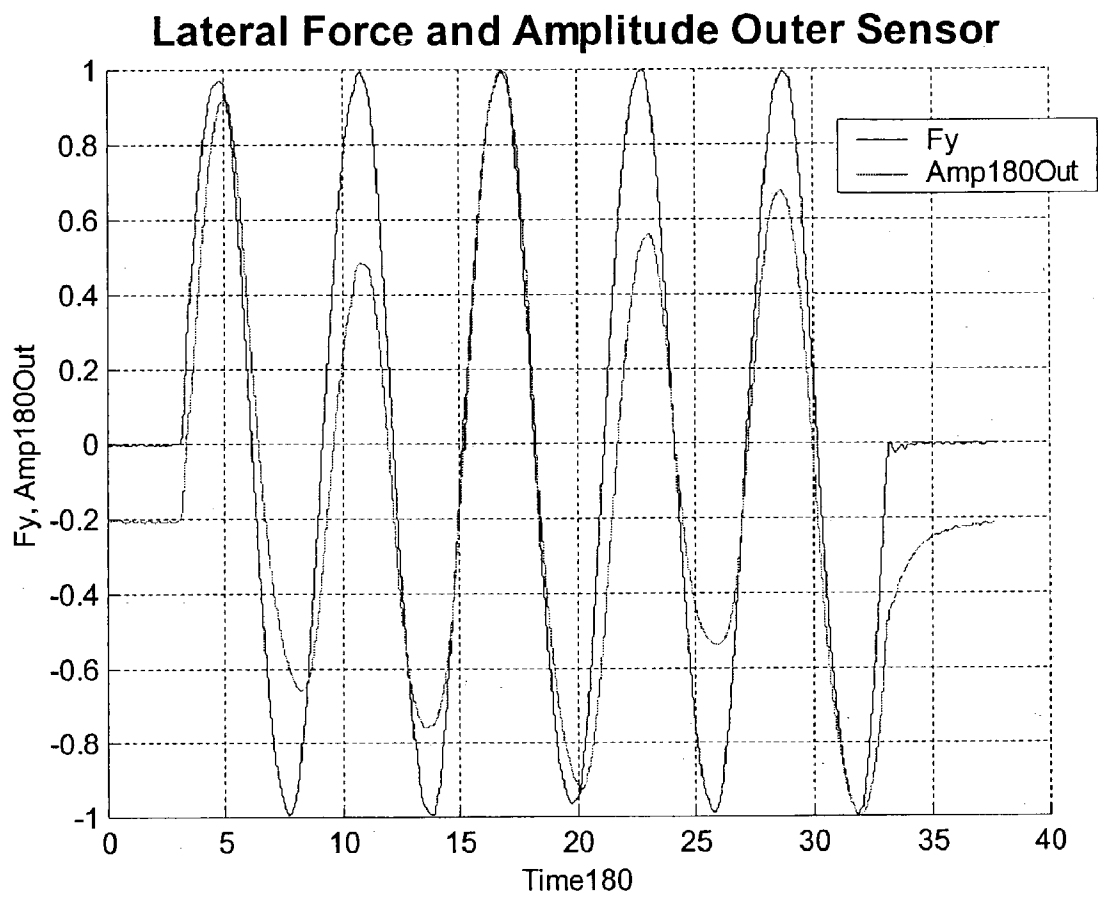


Fig. 8

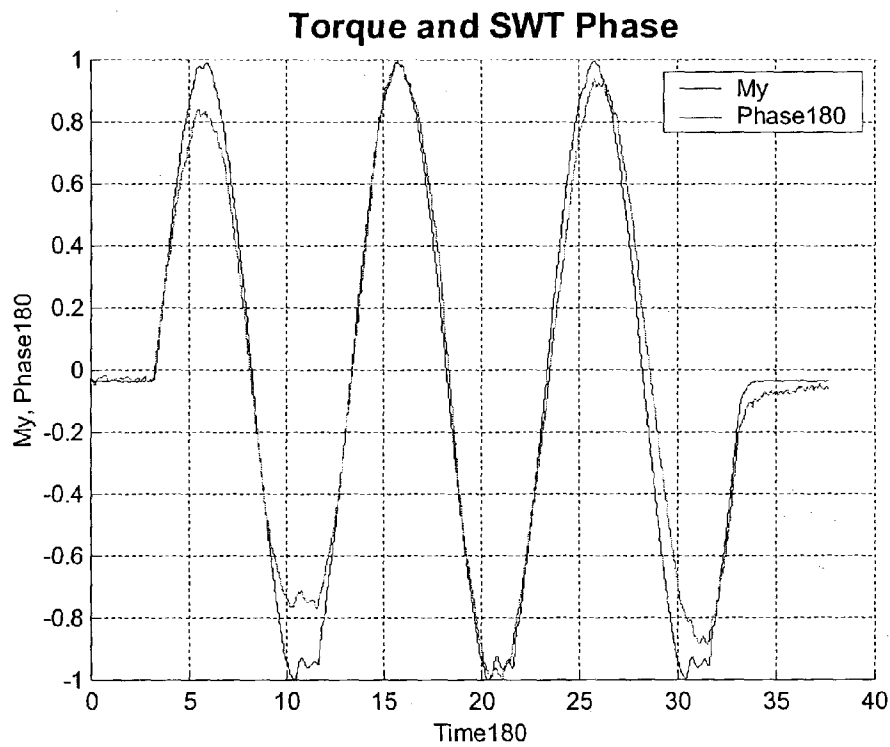


Fig. 9

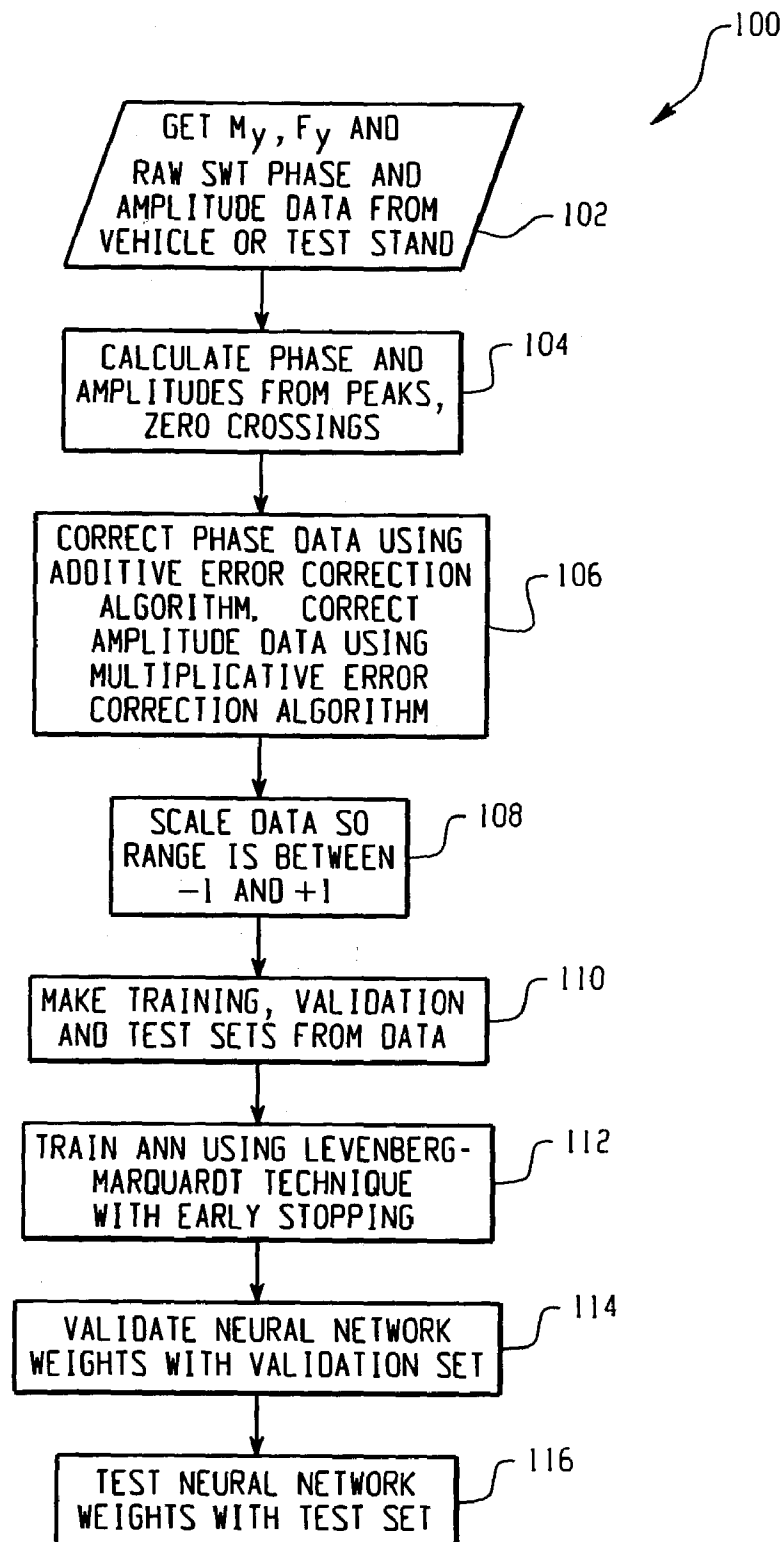
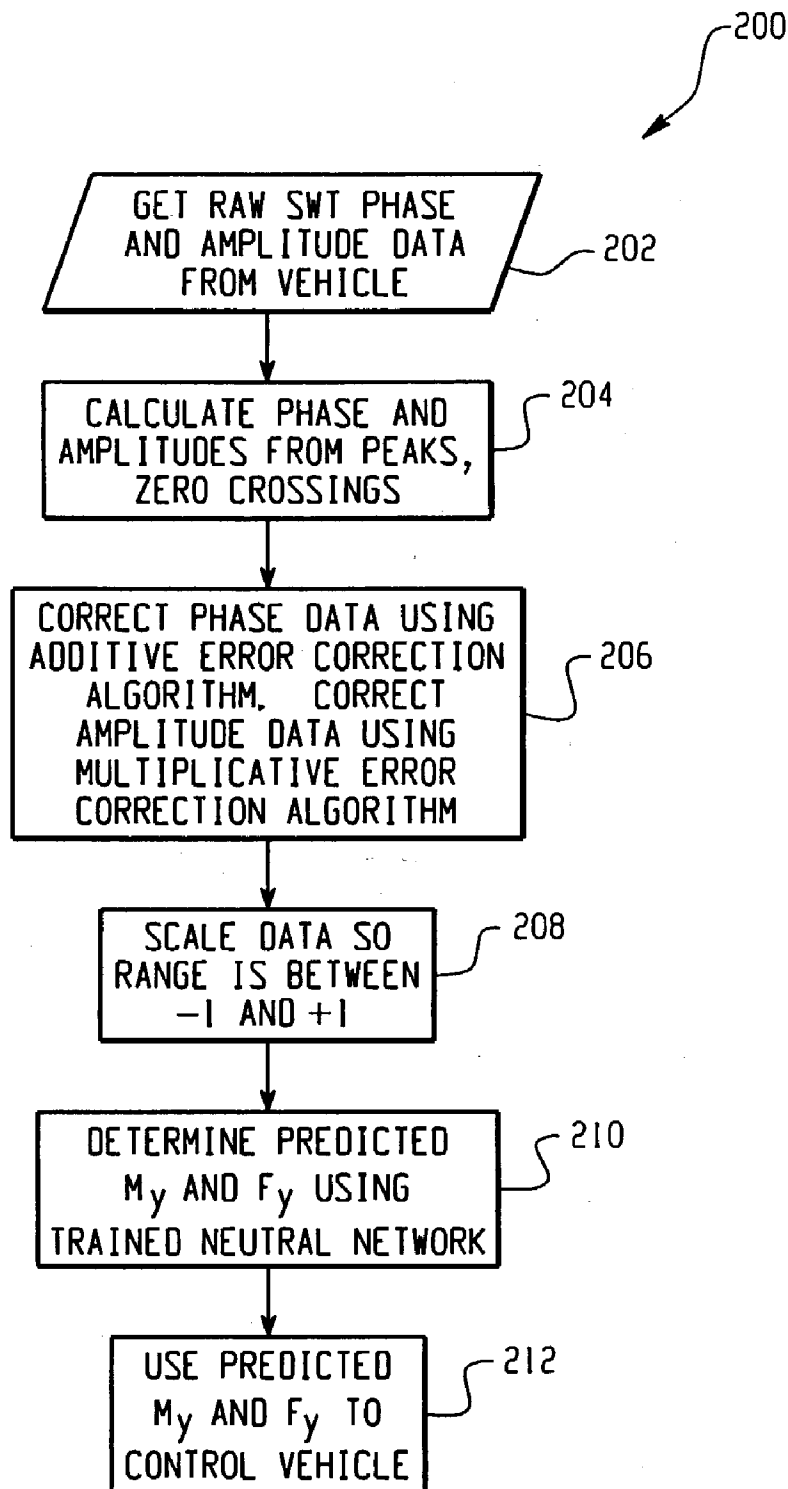


Fig. 10

*Fig. 11*

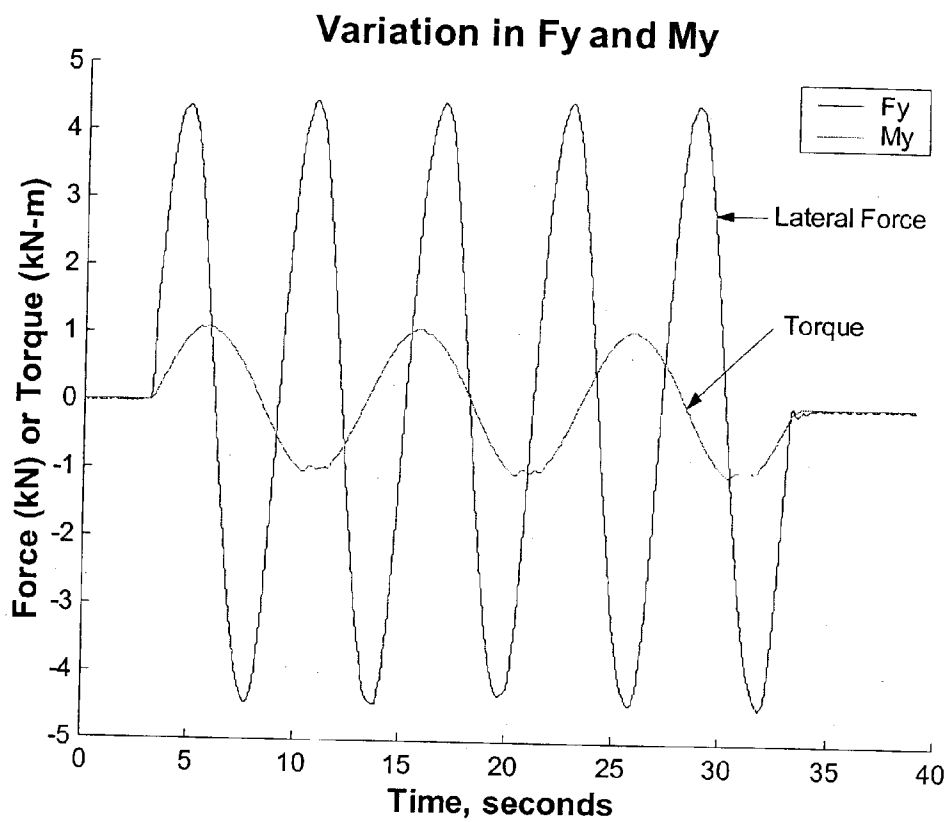


Fig. 12

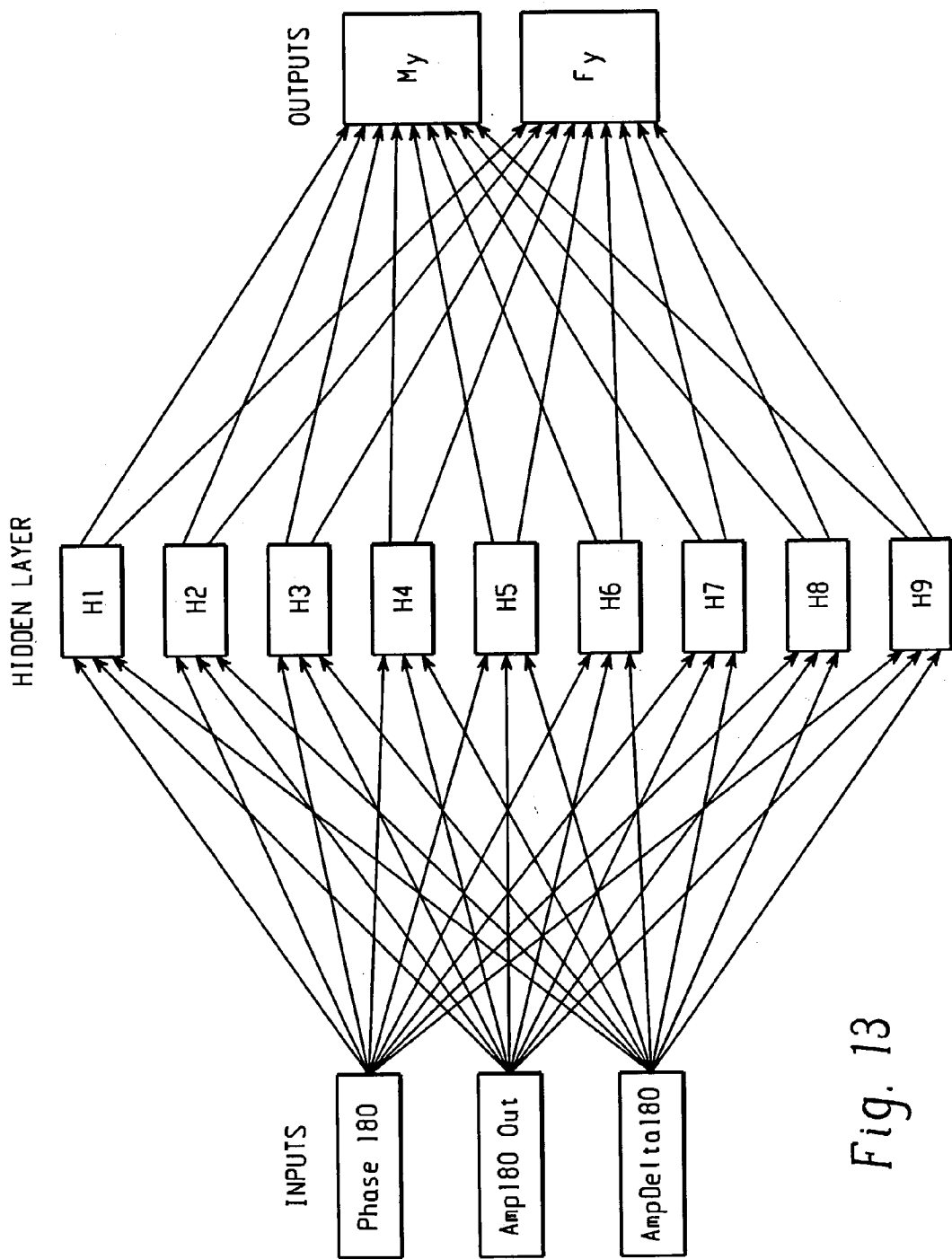


Fig. 13

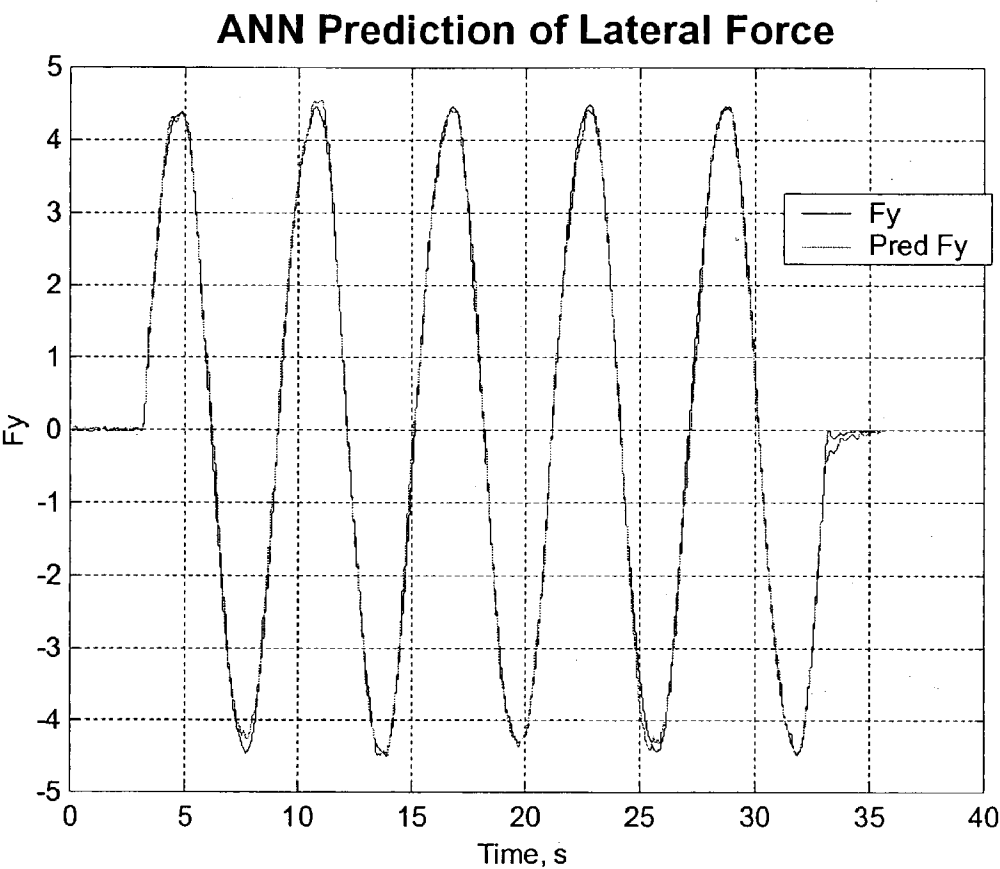


Fig. 14

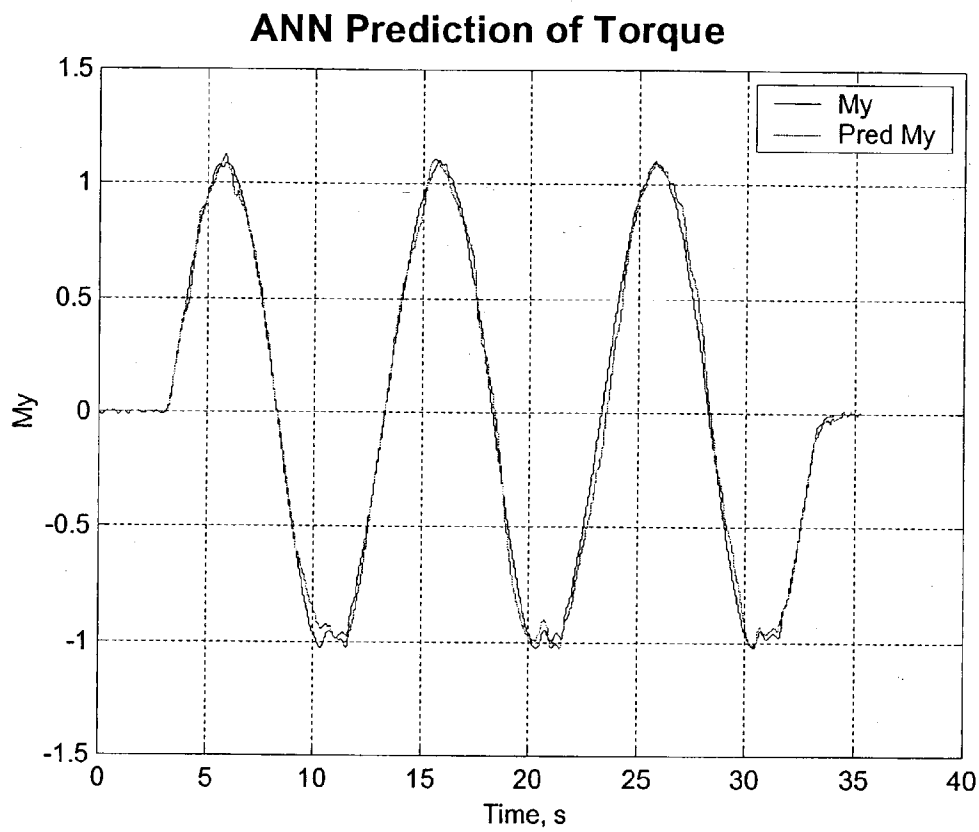


Fig. 15

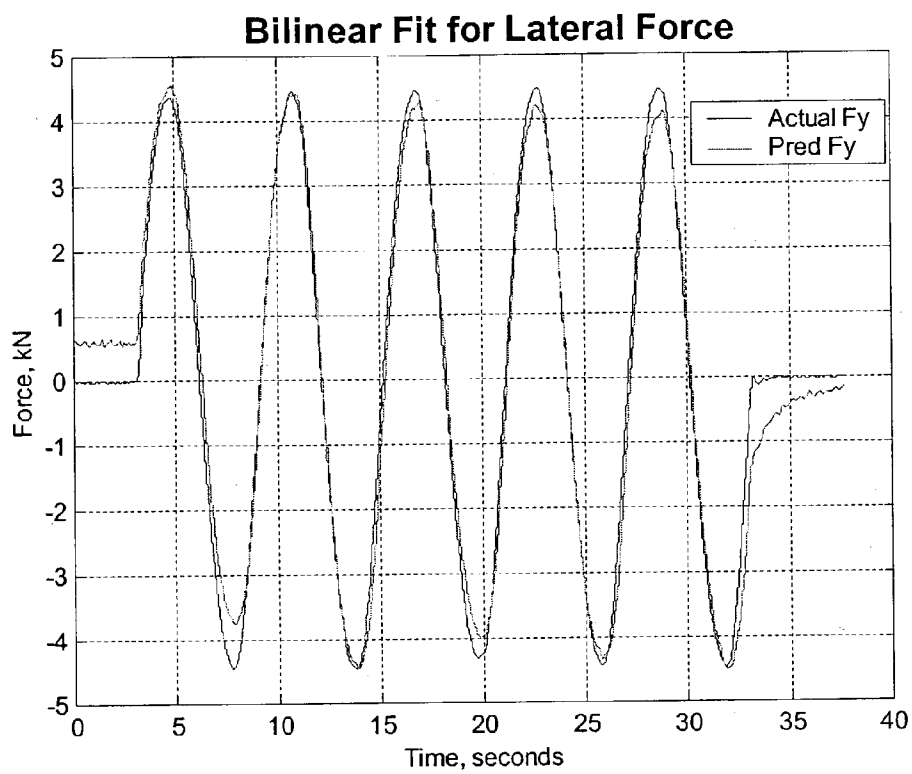


Fig. 16

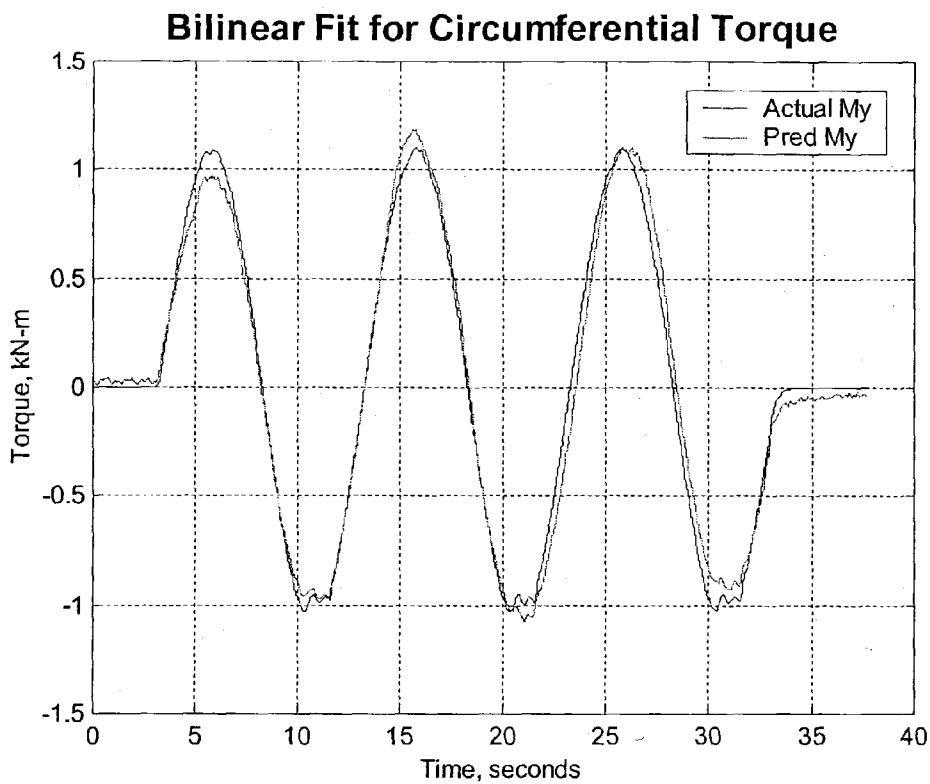


Fig. 17

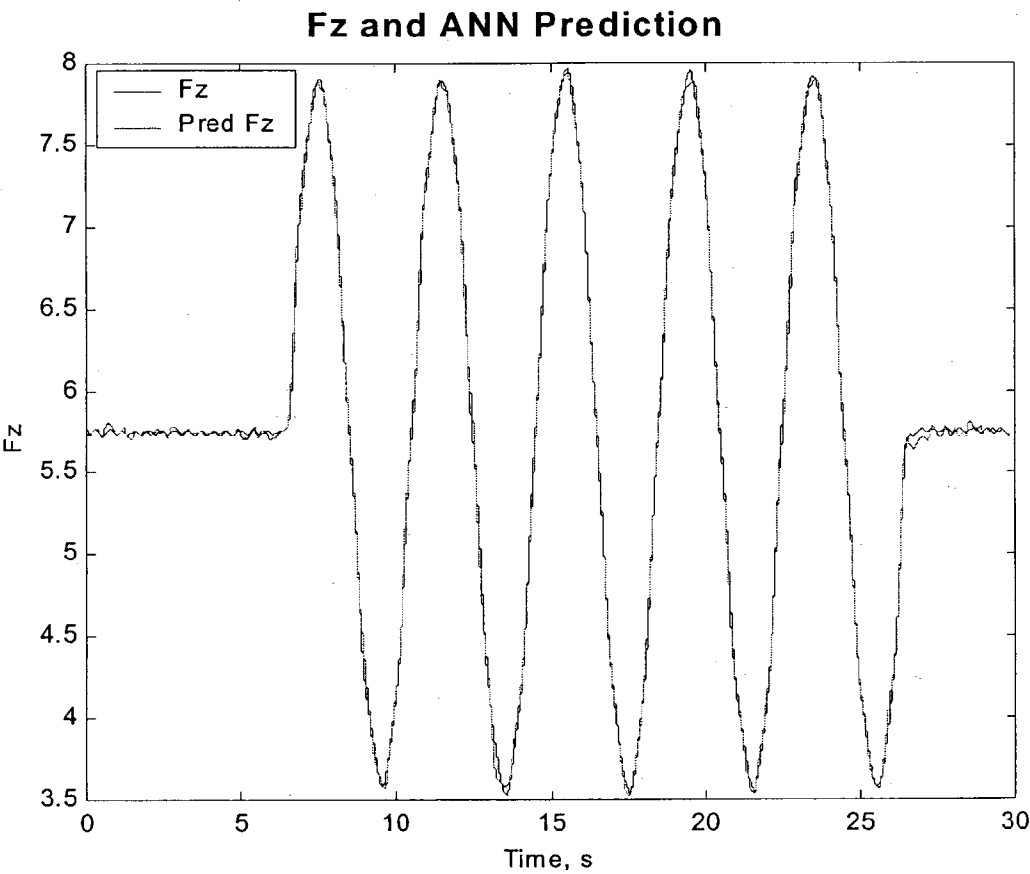


Fig. 18

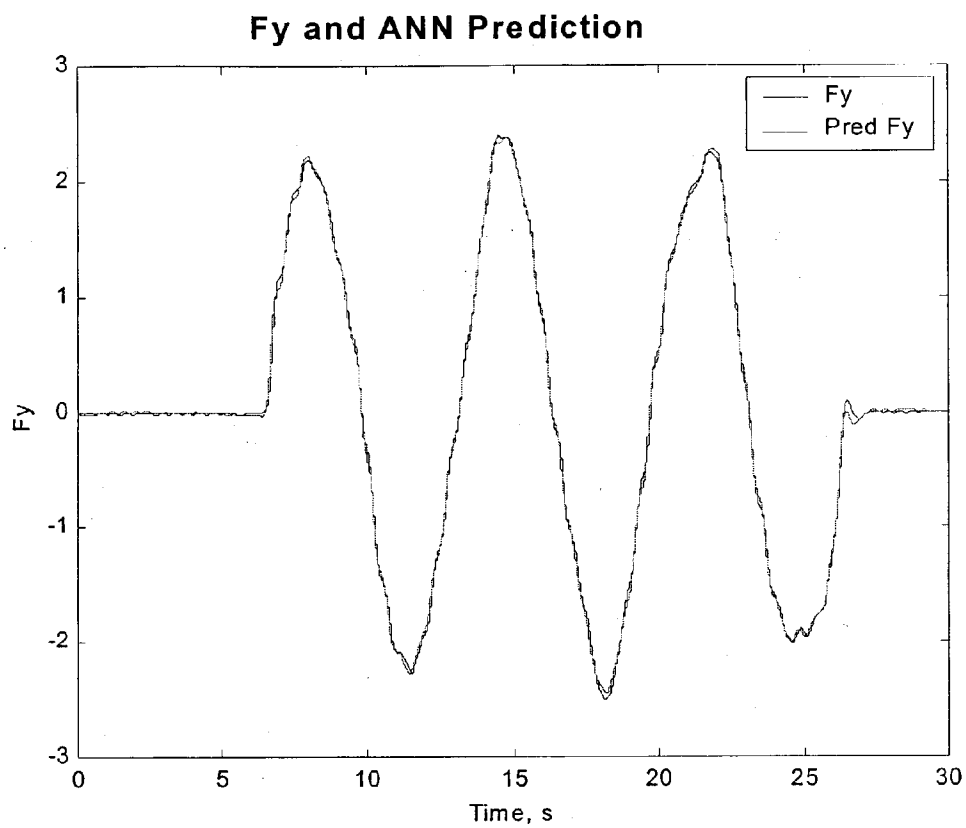


Fig. 19

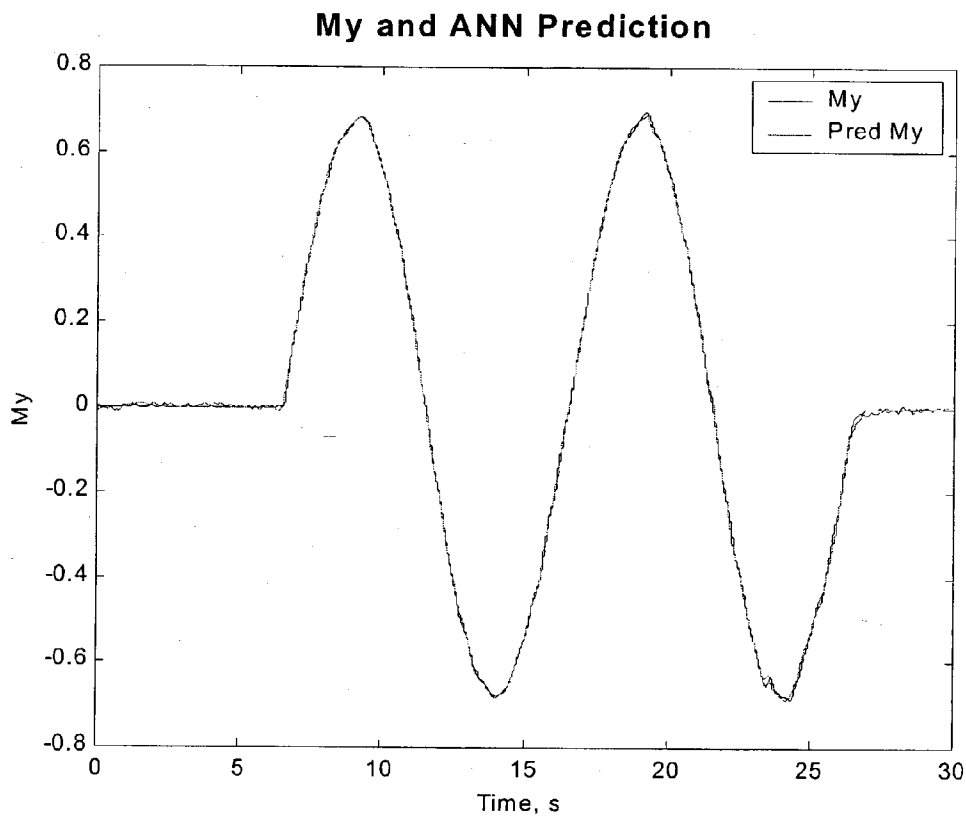


Fig. 20

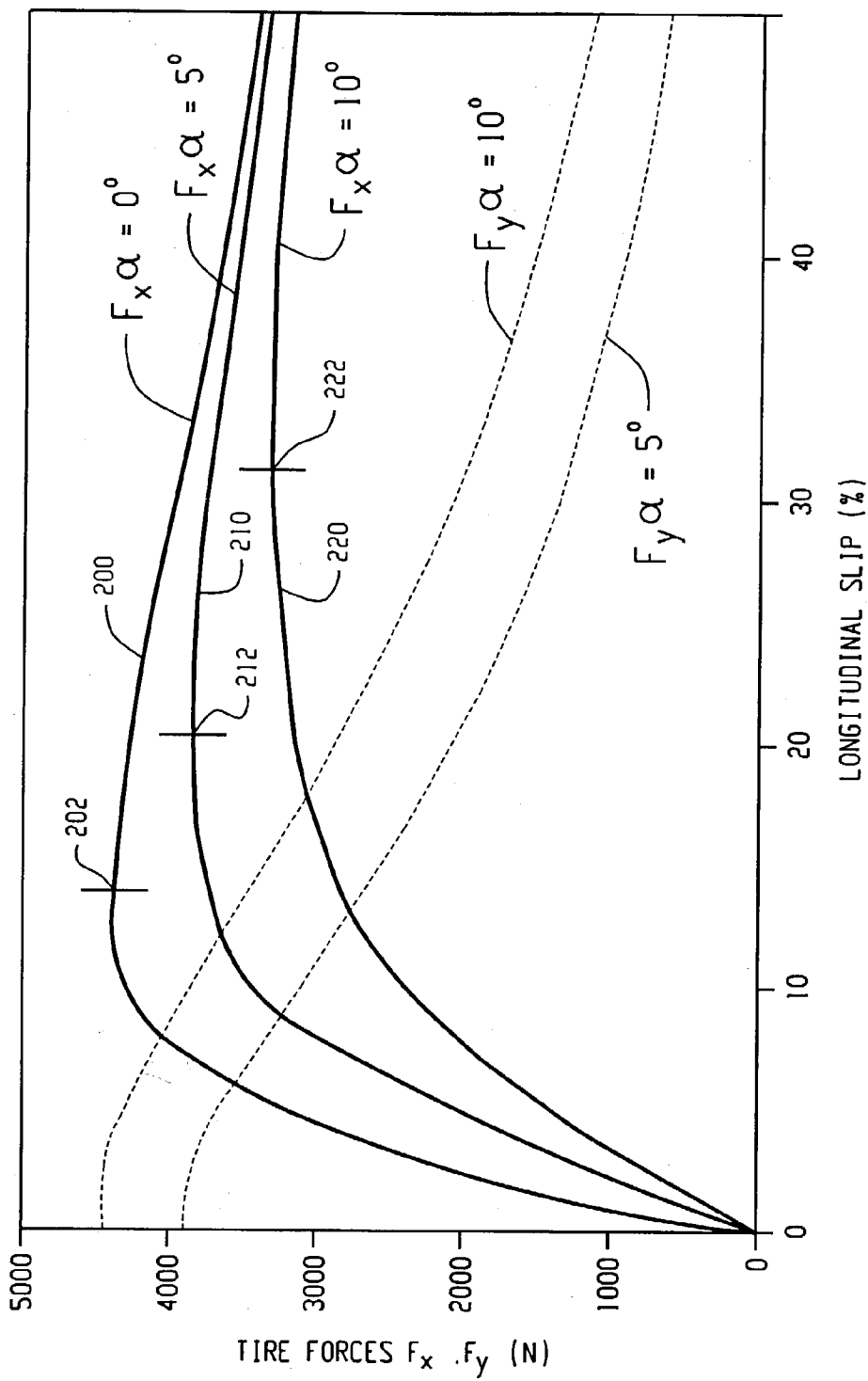


Fig. 21

SYSTEM AND METHOD FOR PREDICTING TIRE FORCES USING TIRE DEFORMATION SENSORS

FIELD OF THE INVENTION

[0001] The present invention relates generally to the field of tire dynamics and more specifically to predicting the forces generated in the tire contact patch from measurements of tire deformations, including separating the lateral force and the circumferential torque using measurements of tire deformations.

BACKGROUND OF THE INVENTION

[0002] U.S. Pat. No. 5,895,854, which is incorporated herein by reference, discloses a vehicle wheel that is provided with a pneumatic (rubber) tire having at least at one predetermined location a rubber mixture that is permeated with magnetizable particles that have been magnetized. As stated in that patent, the tire disclosed therein can be used in a slip regulation system. Preferably, the magnetized locations are located in one or more annular bands in the sidewall of the tire, i.e., in the longitudinal or peripheral direction, and have successive zones of different magnetization in one or more rows disposed at different radii along the peripheral direction of the tire. It was an object of that patent to provide a vehicle wheel having a pneumatic (rubber) tire, with the aid of which the information required for operating a modem vehicle, e.g. wheel rotational speed for ABS (Anti-lock Brake system) and/or longitudinal forces (torsional forces) that act upon the tire for regulating slip, can be made available.

[0003] According to that patent, the generated magnetization and the spatial magnetization differences could be detected with magnetic field sensors and can serve as SWT sensor input signals (sidewall torsion sensor input signals) for slip regulating systems, especially also for SWT systems (sidewall torsion measuring systems). As further stated in that patent, it was previously thought that in order to be able to detect a change of the time span between the passes of the two marks (in one row for ABS or in two rows for SWT) as precisely as possible, it was desired that the magnetization in the peripheral direction be effected as quadrilaterally as possible, i.e. that the magnetization should be substantially homogeneous within a cohesive region (code bars), and above all at the boundaries of this region should change with as great a gradient as possible. In contrast, it was stated that for the conventional ABS systems that detected the wheel rotations, it was sufficient if the magnetization in the peripheral direction of the tire be effected in a sinusoidal manner.

[0004] Thus, a primary function of the SWT system using the SWT sensor has always been to measure the torsional deformation in the tangential direction of the tire and use that torsional deformation to calculate the applied driving or braking torque. However, cornering maneuvers adversely affect the calculation of driving torque or braking torque, because the presence of lateral forces on the tire confounds the measurement of longitudinal torque using the SWT sensor as originally envisioned (using phase differences between the two sensors detecting the magnetic bands in the tire sidewall to calculate torsional deformation). Additionally, the presence of a vertical force on the tire further confounds the measurement of longitudinal torque using the SWT sensor as originally envisioned, although not as severely as lateral force does.

SUMMARY OF THE INVENTION

[0005] The present invention provides a system and method for not only decoupling the lateral and tangential forces to allow the SWT sensor to be used to effectively measure longitudinal torque, but also predicting the lateral force and other forces and torques acting on the tire using the SWT sensors.

[0006] According to the present invention, a system and method are provided for predicting the forces generated in the tire contact patch from measurements of tire deformations, including separating skewed forces, e.g., lateral force and circumferential torque, using measurements of tire deformations.

[0007] According to one aspect of the system of the present invention, a trained processor, e.g., a trained neural network, is used to predict skewed forces, e.g., lateral force and circumferential torque, using measurements of tire deformations. In a first embodiment, a trained neural network is used to predict at least one force acting on the tire, preferably lateral force and circumferential torque. In a second embodiment, a set of bilinear equations are used to predict at least one force acting on the tire, preferably lateral force and circumferential torque.

[0008] It is therefore an advantage of the present invention to provide a system and method for determining circumferential torque using tire deformation sensors, e.g., SWT sensors.

[0009] It is also an advantage of the present invention to provide a system and method for determining lateral force using tire deformation sensors, e.g., SWT sensors.

[0010] It is therefore another advantage of the present invention to provide a system and method for decoupling lateral force and circumferential torque in measurements from tire deformation sensors, e.g., SWT sensors.

[0011] It is a further advantage of this invention to provide a system and method for determining vehicle yaw rate from tire deformation sensors, e.g., SWT sensors, thereby eliminating the need for a separate yaw rate sensor.

[0012] It is yet another advantage of the present invention to provide a system and method for determining vehicle speed from tire deformation sensors, e.g., SWT sensors, thereby eliminating the need for a separate speed sensor.

[0013] It is still another advantage of the present invention to provide a system and method for using a trained neural network to determine any combination or permutation of one or more of any of the following from tire deformation sensors, e.g., SWT sensors: the lateral force acting on the tire, the circumferential torque acting on the tire, the longitudinal force acting on the tire, the vertical force acting on the tire, and forces and/or torques having any one or more of the foregoing as components thereof.

[0014] It is further still another advantage of the present invention to provide a system and method for using bilinear equations to determine any combination or permutation of one or more of any of the following from tire deformation sensors, e.g., SWT sensors: the lateral force acting on the tire, the circumferential torque acting on the tire, the longitudinal force acting on the tire, the vertical force acting on

the tire, and forces and/or torques having any one or more of the foregoing as components thereof.

[0015] It is another advantage of the present invention to decouple circumferential torque of a tire from lateral forces and vertical forces acting on the tire.

[0016] It is still another advantage of the present invention to provide a system and method for determining any combination or permutation of one or more of any of the following from tire sidewall deformation sensors, e.g., SWT sensors: the lateral force acting on the tire, the circumferential torque acting on the tire, the longitudinal force acting on the tire, the vertical force acting on the tire, and forces and/or torques having any one or more of the foregoing as components thereof.

[0017] These and other advantages of the present invention will become more apparent from a detailed description of the invention.

BRIEF DESCRIPTION OF THE DRAWINGS

[0018] In the accompanying drawings, which are incorporated in and constitute a part of this specification, embodiments of the invention are illustrated, which, together with a general description of the invention given above, and the detailed description given below serve to example the principles of this invention.

[0019] FIG. 1 is a perspective view of a vehicle showing various forces and torques;

[0020] FIG. 2 is a schematic block diagram of a system of the present invention;

[0021] FIG. 3 is a side view of a tire having magnetic bands of alternating polarity and corresponding sensors used with the system and method of the present invention;

[0022] FIG. 4 is a perspective view of a mounting bracket fixed to a suspension strut and holding two magnetic sensors in close proximity to the magnetic sidewall of the tire;

[0023] FIG. 5 is a close up view of the mounting bracket and sensors shown in FIG. 5;

[0024] FIG. 6 is a front view of the tire, suspension strut, and sensors showing the effects of a lateral force, with the tire viewed in a section taken vertically;

[0025] FIG. 7 is a close up view of the tire and sensors of FIG. 6;

[0026] FIG. 8 is a data plot of SWT sensor amplitude taken in the presence of lateral force and circumferential torque, showing that in the presence of torque SWT sensor amplitude is a relatively poor predictor of lateral force;

[0027] FIG. 9 is a data plot of SWT sensor amplitude taken in the presence of lateral force and circumferential torque, showing that the presence of lateral force causes a cross-term error when using SWT sensor phase difference as a predictor of circumferential torque;

[0028] FIG. 10 is a flow chart showing the general procedure used to train the neural network of the present invention;

[0029] FIG. 11 is a flow chart showing the general procedure for using the trained neural network of the present invention to predict lateral force and circumferential torque;

[0030] FIG. 12 is a data plot showing the lateral force and circumferential torque applied to the tire during data acquisition;

[0031] FIG. 13 is a schematic block diagram showing the structure of the neural network trained in Example 1;

[0032] FIG. 14 is a data plot showing measured lateral force and the lateral force predicted by the trained neural network of Example 1;

[0033] FIG. 15 is a data plot showing measured circumferential torque and the circumferential torque predicted by the trained neural network of Example 1;

[0034] FIG. 16 is a data plot showing measured lateral force and the lateral force predicted by the bilinear equations of Example 2;

[0035] FIG. 17 is a data plot showing measured circumferential torque and the circumferential torque predicted by the bilinear equations of Example 2;

[0036] FIG. 18 is a data plot showing measured vertical force and the vertical force predicted by the trained neural network of Example 3;

[0037] FIG. 19 is a data plot showing measured lateral force and the lateral force predicted by the trained neural network of Example 3;

[0038] FIG. 20 is a data plot showing measured circumferential torque and the circumferential torque predicted by the trained neural network of Example 3;

[0039] FIG. 21 shows a plurality of coefficient of dynamic friction (μ) versus percent slip (μ -slip) curves at various steering angles showing the significant effect that even small lateral forces can have on the location of the peak of the μ -slip curve;

[0040] FIG. 22 is a data plot showing measured vertical force and the vertical force predicted by the bilinear equations of Example 4;

[0041] FIG. 23 is a data plot showing measured lateral force and the lateral force predicted by the bilinear equations of Example 4; and

[0042] FIG. 24 is a data plot showing measured circumferential torque and the circumferential torque predicted by the bilinear equations of Example 4.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENT

[0043] "Circuit communication" as used herein is used to indicate a communicative relationship between devices. Direct electrical and optical connections and indirect electrical and optical connections are examples of circuit communication. Two devices are in circuit communication if a signal from one is received by the other, regardless of whether the signal is modified by some other device. For example, two devices separated by one or more of the following—transformers, optoisolators, digital or analog buffers, analog integrators, other electronic circuitry, fiber optic transceivers, or even satellites—are in circuit communication if a signal from one reaches the other, even though the signal is modified by the intermediate device(s). As a final example, two devices not directly connected to each other, but both capable of interfacing with a third device,

e.g., a CPU, are in circuit communication. As used herein, "input" refers to either a signal or a value and "output" refers to either a signal or a value.

[0044] Referring now to **FIG. 1**, the forces referred to herein are shown schematically. In that figure, a vehicle **10** is shown schematically along with the longitudinal force F_x , the longitudinal (circumferential) torque M_y , and the lateral force F_y acting on the tires. Although not shown in **FIG. 1**, another force of interest is the vertical force F_z which is perpendicular to the longitudinal force F_x and the lateral force F_y .

[0045] Referring now to **FIG. 2**, a vehicle control system **20** according to the present invention is shown schematically. In the broadest sense, the vehicle control system **20** comprises a force prediction unit **22** to be placed in circuit communication with at least one tire sidewall deformation sensor. Preferably, the tire sidewall deformation sensor is a magnetic tire sidewall torsion (SWT) sensor. The force prediction unit **22** has a preprogrammed processor (not shown) that receives input from the at least one SWT sensor and at least one other sensor input and performs data analysis by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the SWT input and the at least one other sensor input an output corresponding to a predicted circumferential torque and/or longitudinal force and/or lateral force and/or vertical force acting on the tire. The force prediction unit **22** may also perform any necessary signal conditioning and data processing associated with the SWT sensor and the other sensor.

[0046] With respect to **FIG. 2**, in a preferred embodiment, the force prediction unit **22** is placed in circuit communication with a pair of magnetic SWT sensors **26, 28** for each tire **30** of the vehicle **20**; however, the force prediction unit **22** may be used with as little as one SWT sensor **26** on a single tire **30** and another sensor, e.g., another SWT sensor **28** or an ABS speed sensor (not shown) to provide force predictions about that one tire **30**. Preferably, the force prediction unit **22** is placed in circuit communication with a control unit **32**, which is in circuit communication with and affects the dynamic state of the vehicle **20** via one or more actuators **34**. Examples of control units **32** and actuators **34** known to those in the art include combinations and permutations of one or more of the following: an ABS control unit with braking actuators, a traction control system (TCS) control unit with braking and throttle actuators, an electronic stability control (ESC) (also known as an integrated vehicle dynamics (IVD)) control unit with braking and throttle actuators, a locked differential control unit, a suspension control unit, a brake assist control unit with braking actuators, an intelligent cruise control unit with vehicle throttle actuators, a steering assist control unit with steering actuators, a deflation detection control unit, a navigation control unit, a rollover prevention control unit, and a brake-by-wire control unit with braking actuators. Significantly, these exemplary control units **32** and actuators **34** require one of more of the following sensors—a longitudinal accelerometer (for longitudinal force and/or acceleration), a lateral accelerometer (for lateral force and/or acceleration), a vertical load sensor, wheel speed sensors, and a yaw rate sensor, all of which can be replaced by one or more SWT sensors coupled with the teachings of the present invention.

[0047] The force prediction unit **22** can be implemented with various combinations of analog and digital circuitry, processors, and the like. The control unit can be implemented with separate circuitry and/or processor(s) or with circuitry and/or processor(s) used to implement the force prediction unit **22**. Preferably, the data processing and data analysis portions of the force prediction unit **22** are implemented in a single processor, with the signal conditioning being performed in dedicated analog circuitry (not shown).

[0048] Referring now to **FIG. 3**, a pair of SWT sensors **26, 28** is shown schematically with the corresponding magnetic tire **30**. As shown schematically in **FIG. 3**, the magnetic tire **30** used with the SWT sensors **26, 28** preferably has a number of alternating bands **38** of magnetic polarity. The magnetic tires **30** can be made in any number of ways, e.g., as taught in U.S. Pat. No. 5,895,854, as taught in copending U.S. patent application Ser. No. 09/347,757, which is incorporated herein by reference, or in any number of other ways, e.g., providing alternating bands of premagnetized thin material, embedding adjacent alternating magnetic bands into the sidewall of a green tire, and curing the green tire. The SWT sensors **26, 28** themselves are preferably magnetic sensors, e.g., magneto-resistive (MR) sensors, Hall effect sensors, or flux gate sensors, positioned close enough to the magnetic regions of the sidewall of tire **30** to interact therewith. MR sensors have the advantages of allowing a moderate air gap and have been extensively tested. Flux gate sensors have the advantage of allowing an air gap of between one to two inches. Hall effect sensors have the disadvantage of requiring a relatively small air gap. If two SWT sensors are used, one sensor **26** is preferably positioned near the tread **40** and the other sensor **28** is preferably positioned near the bead **42**. If only one SWT sensor is used with another sensor, e.g., an ABS speed sensor, the SWT sensor **26** is preferably positioned closer to the tread **40** than the bead **42** to provide greater sensitivity to torsional deformation.

[0049] Referring now to **FIG. 4** and **FIG. 5**, the mounting of the sensors **26, 28** to a vehicle suspension strut **50** is shown. Preferably the sensors **26, 28** are mounted to a suspension strut **50** via a mounting bracket **52**. In **FIG. 4** and **FIG. 5**, the sensors **26, 28** are model number KMZ10A magneto-resistive (MR) sensors, available from Philips. Mounting bracket **52** preferably is configured so that the flat end portion of hall effect sensors **26, 28** are substantially parallel to the sidewall of magnetic tire **30**. Preferably, the flat end portion of MR sensors **26, 28** are 12.5 mm from the surface of the sidewall of magnetic tire **30** when there are no lateral forces present acting on the tire **30**. With lateral forces present, the air gap can be expected to range from about 8 mm to about 25 mm. Because the sidewall of a tire typically has a pronounced curvature, the mounting bracket **52** preferably provides a pair of skewed (i.e., not parallel) surfaces **54, 56** for the sensors **26, 28** respectively. The mounting bracket **52** may be secured to suspension strut **50** by any suitable means, such as integrally forming mounting bracket **52** with strut **50**, using suitable fasteners, e.g., bolts **58** and nuts **60** as shown in **FIGS. 4 and 5**, or by any other suitable means. The sensors **26, 28** may be secured to mounting bracket **52** by any suitable means, such as using suitable fasteners, e.g., bolts **62** and nuts **64** as shown in **FIGS. 4 and 5**, or by any other suitable means. Wires **66, 68** place sensors **26, 28** in circuit communication with the force prediction unit **22**.

[0050] The mounting bracket also preferably secures sensors 26, 28 so that the line segment between them is as parallel as is practicable to the magnetic interface line between successive magnetic bands 38 of magnetic tire 30. In this way, in the free rolling state, the sensors 26, 28 preferably detect the transition from one band 38 to the next at the same time, i.e., there will be no or a small phase difference between the two sensor signals. A torsional deformation, e.g., caused by application of a brake, takes the form of the tire tread 40 rotating with respect to the tire bead 42, so that the tire magnetic interface line is no longer parallel to the line segment between sensors 26, 28. This torsional deformation is detected by the SWT sensors 26, 28 as a change in the phase shift between the two signals, i.e., the transition from one magnetic band 38 to the next will be detected by one sensor sooner or later than it would otherwise be detected by that sensor with respect to the other sensor. The signals from the sensors 26, 28 in this configuration are sinusoidal signals.

[0051] The sensors 26, 28 in FIG. 4 and FIG. 5 are positioned at the 180° location (at the 12 o'clock position), which provides the most sensitivity for decoupling circumferential torque and lateral force, F_y . Additionally, it is preferable to position a second pair of SWT sensors per tire (not shown) at either the 90° or the 270° position (at the 3 o'clock or 9 o'clock position) to provide the most sensitivity for decoupling circumferential torque and vertical force, F_z . However, providing sensors at the 90° or the 270° position has proven to be challenging because sensors in either of those positions tend to be exposed to forces that misalign the sensors or cause the sensor supports to bend or break off. In the alternative, a single pair of SWT sensors positioned at 135° is believed to provide information to decouple circumferential torque from both lateral force, F_y , and vertical force, F_z . Also in the alternative, a single additional outer sensor can be used at either the 90° or the 270° position rather than using an additional pair of sensors in that position. In that case, the phase of the sensor at the 90° or 270° position would be taken with respect to the inner sensor at the 180° position.

[0052] The force prediction unit 22 preferably accepts as inputs at least (a) a phase difference input, relating to (and preferably representing) a change in phase between the signals of the two sensors 26, 28 caused by torsional deformation in the sidewall of the tire and (b) a peak amplitude input from the outer sensor 26 relating to (and preferably representing) the length of the changing air gap between the sensor 26 and the sidewall. More preferably, the force prediction unit 22 also accepts as additional inputs (c) a value relating to (and preferably representing) the speed of the vehicle (which can be determined from the period of each region of one of the SWT sensors, inverted and scaled by the radius of the tire) and (d) a delta input relating to (and preferably representing) the difference between the peak amplitude signal from the outer sensor 26 and the peak amplitude signal of the inner sensor 28. The speed input allows the force prediction unit to take into account the effects on the sidewall of centrifugal forces at higher speeds and the effects of relaxation phenomenon on the tire at lower speeds. Additionally, certain cross terms such as phase difference input multiplied by peak amplitude input allow force prediction units to be trained with a very low mean sum of squared errors. Thus, force prediction units according to the present invention, such as neural networks and

bilinear equation sets, can have as inputs any one or more of the following: one phase difference input for each sensor pair, a peak amplitude input for each sensor, preferably each outer sensor in the pair, a speed input, a delta peak input for each sensor pair, and a cross term (phase difference input multiplied by peak amplitude input) for each sensor pair, among others, with sensor pairs being located at 90° and/or 135° and/or 180° and/or 270°, depending on the force(s) and/or torque(s) to be predicted.

[0053] Referring now to FIG. 6 and FIG. 7, the effect on the positional relationship between the tire 30 and sensors 26, 28 by a lateral force is shown schematically. The tire 30 and rim 70 are shown in dashed lines in the free rolling state and in solid lines under the influence of a lateral force. In short, the lateral force causes the distance between the sensors 26, 28 and the tire 30 to be greater. A lateral force in the opposite direction to the force shown in FIG. 6 will cause the distance between the sensors 26, 28 and the tire 30 to be less. These differences in distance are reflected in a change in amplitude of the signals from sensors 26, 28.

[0054] The relatively straightforward conceptual framework for the SWT sensors set forth in the preceding two paragraphs is greatly complicated in application because the lateral force and longitudinal force are coupled to some degree. This is illustrated by FIG. 8 and FIG. 9. FIG. 8 shows plots of normalized lateral force (in the presence of circumferential torque) and normalized amplitude of the outer SWT sensor 26 versus time (data from a Conti Sport Contact, 245/40 R18 magnetic sidewall tire collected with an MTS Model 860 tread wear machine (available from MTS Systems Corporation) in accordance with the data collection section of Example 1). As shown in FIG. 8, in the presence of circumferential torque, the normalized amplitude of the outer SWT sensor 26 is a poor predictor of lateral force. Similarly, FIG. 9 shows plots of normalized circumferential torque (in the presence of lateral force) and normalized phase-shift between the two SWT sensors 26, 28 versus time (data from a Conti Sport Contact, 245/40 R18 magnetic sidewall tire collected with an MTS Model 860 tread wear machine in accordance with the data collection section of Example 1). As shown in FIG. 9, the presence of lateral force apparently causes a cross-term error when using the normalized phase difference between the two SWT sensors 26, 28 as a predictor of circumferential torque.

[0055] The present invention overcomes these drawbacks by using the force prediction unit 22 of the present invention, which uses inputs from both SWT sensors 26, 28 to determine both the circumferential torque and the lateral force acting on the tire.

[0056] In a first embodiment of the force prediction unit 22 of the present invention, the processor of the force prediction unit 22 implements a neural network either in software or in hardware. Preferably the neural network is configured to determine both the circumferential torque and the lateral force acting on the tire; however, the neural network can be configured to determine any combination or permutation of one or more of any of the following: the lateral force acting on the tire, the circumferential torque acting on the tire, the longitudinal force acting on the tire, the vertical force acting on the tire, and forces and/or torques having any one or more of the foregoing as components thereof. Preferably, the magnitude (amplitude) of the outer

SWT sensor **26** and the phase difference between the signals of the two SWT sensors **26, 28** are input to the neural network, with the desired parameters being output. Even more preferably, the difference in magnitude (amplitude) between the signal from the outer SWT sensor **26** and the signal from the inner SWT sensor **28** is used as an additional input. The neural network of the force prediction unit **22** is preferably a multi-layer perceptron, and is even more preferably a multi-layer perceptron having one input layer, one hidden layer (having, e.g., 5-20 nodes), and one output layer. As to transfer functions between layers, a nonlinear, hyperbolic tangent sigmoidal transfer function is preferably used between the input layer and the hidden layer, and a linear transfer function is preferably used between the hidden layer and the output layer. The hyperbolic tangent sigmoidal transfer function is preferably implemented as follows:

$$\text{tansig} = \frac{2}{e^{-2n} + 1} - 1$$

[0057] where

[0058] $n = W \cdot p + b$

[0059] W = a matrix of weights,

[0060] b = a matrix of bias values

[0061] p = a matrix of input values

[0062] $W \cdot p$ represents matrix multiplication

[0063] As expected, the neural network in the force prediction unit **22** must be trained using previously collected data. This training is exemplified by **FIG. 10**, which is a flowchart **100** showing generally how the neural network in the force prediction unit **22** is trained using previously collected data. Initially, data must be collected, at step **102**. In general, the desired forces and torques are collected, e.g., from an instrumented hub or from a dynamometer, along with the raw SWT sensor data. In the preferred embodiment, the circumferential torque and the lateral force acting on the tire, and the raw SWT sensor data, are collected with an MTS Model 860 tread wear machine (available from MTS Systems Corporation) with the frequency of the circumferential torque and lateral force being different prime numbers to provide a full spectrum of measured and interacting torques and forces. Data is collected, for example, at between 25,000 and 1,000,000 samples per second, and typically at 50,000 samples per second.

[0064] Next, at step **104**, the raw sinusoidal SWT sensor data is processed to calculate the inputs to the neural network. In the preferred embodiment, the phase and two amplitudes are calculated from the peaks and zero-crossings of the raw SWT sensor data. More specifically,

[0065] (a) the phase difference is determined as follows: (i) the mean value is subtracted from all the data, (ii) at each peak region and at each valley region a polynomial is fit along the peak or valley, (iii) the maximum/minimum of the resulting polynomial is determined (by, e.g., setting the differential to zero to determine the horizontal tangent), (iv) the time of a peak/valley of one signal is subtracted from the time of the peak/valley of the other signal, and

(v) the resulting difference is divided by the corresponding "half-period" (the time from the previous peak/valley to that valley/peak) to make the phase difference independent of vehicle velocity;

[0066] (b) the amplitude of the signal from the outer SWT sensor **26** is determined as follows: (i) the mean value is subtracted from all data from sensor **26**, (ii) at each peak region and at each valley region a polynomial is fit along the peak or valley, (iii) the maximum/minimum of the resulting polynomial is determined (by, e.g., setting the differential to zero to determine the horizontal tangent), (iv) the processed signal is rectified (by, e.g., taking the absolute value of each data point), and (v) the amplitude of the fit polynomial at each maximum is used as the amplitude of that signal;

[0067] (c) the peak difference between the two SWT signal amplitudes is determined as follows: (a) the peak amplitude of the signal from the inner sensor **28** is calculated in accordance with step (b) above is subtracted from the peak amplitude of the signal from the outer sensor **26** as determined at (b) above.

[0068] The sinusoidal nature of the signals from the sensors facilitates using the fit polynomial in place of the actual sensor data. Additionally, using the fit polynomial for the phase and amplitude inputs tends to smooth or remove any noise that might otherwise cause erroneous calculations.

[0069] Having calculated the phase and two amplitudes, next these inputs are corrected at step **106** using various correction methods. An exemplary correction method is as follows: For a tire magnetized so that there are **48** north and **48** south poles per circumference, the inner and outer SWT sensor signals will be very much like sinusoidal waves with a frequency of 48 wavelengths per tire revolution; i.e., there are 48 "peak" amplitudes and 48 "valley" amplitudes in every tire revolution. If the mean is subtracted from the signal, each revolution would produce 96 "zero" crossings. In addition, if the signal is rectified, turning each valley into a peak, there would be 96 peak amplitudes. NumPoles represents the number of North and South magnetic poles around the circumference of the tire. Thus, for this particular tire the parameter NumPoles is 96. For a uniform velocity, i.e., for a constant speed with no torques or lateral forces acting, the time difference between the zero crossings, or the time difference between the peak amplitudes, defines the pole pitch. If the pole spacing is uniform, there would be 360 degrees/96=3.75 degrees or $2\pi/96=0.0654$ radians between each pole. In practice, however, the pole spacing is rarely perfectly uniform for a particular tire. Thus, there is some error associated with each of the 96 pole spacing values. But this error is due to the geometry and magnetization process applied to the particular tire. The error for each pole spacing value repeats itself with each revolution of the tire. These errors affect not only the pole pitch values, but also the phase differences between the inner and outer SWT sensor signals. With no torques or lateral forces acting on the tire, the phase differences between these two signals will consist of 96 constant values. Thus, the following method can be used to correct the phase errors between poles:

[0070] First, (1) SWT phase data is collected at a uniform velocity (no torques or lateral forces). Then, (2) from the vector of phase data collected in (1), calculate the zero

crossings (or “mean” crossings) and the peaks and valley amplitudes. Next, (3) rectify the data so that valley amplitudes become peak amplitudes. Then, (4) partition the vectored data into NumPoles sets and ensemble average N of the sets, i.e.:

pole number	1	2	3	...	k	...	NumPoles
set 1	P ₁₁	P ₁₂	P ₁₃	...	P _{1k}	...	P _{1NumPoles}
set 2	P ₂₁	P ₂₂	P ₂₃	...	P _{2k}	...	P _{2NumPoles}
...	...	...	...	...	...	...	...
set j	P _{ji}	P _{j2}	P _{j3}	...	P _{jk}	...	P _{jNumPoles}
set N	P _{N1}	P _{N2}	P _{N3}	...	P _{Nk}	...	P _{NNumPoles}
Average	ave ₁	ave ₂	ave ₃	...	ave _k	...	ave _{NumPoles}

[0071] Next, (5) calculate the average (grand mean) of the ensemble averages. Then, (6) subtract the grand mean from the Average vector to form a vector of correction values. Next, (7) subtract the correction values from entire matrix of data collected under the influence of various torques and forces, i.e., correct all the data that has been previously collected. Finally, (8) reshape matrix of data back into a vector.

[0072] In the alternative, (9) the data can be filtered data using a running average where the number of points averaged is between 2 and NumPoles.

[0073] The amplitude data is corrected in a similar fashion using a multiplicative error correction routine. Perform the same steps 1 through 5 as described in the additive correction error algorithm described above, but apply the steps to the vector of SWT amplitude data. In step 6 however, instead of subtracting the grand mean from the Average, divide the grand mean into the Average to form the vector of correction values. In step 7, multiply the entire matrix of data by the vector of correction values, thereby correcting all the amplitude data. Steps 8 and 9 are performed the same as for the additive correction value.

[0074] Next, at step 108, the corrected phase data and two corrected amplitudes are normalized, i.e., scaled to between -1 and +1 by ordinary techniques known to those in the art.

[0075] Then the large data set is divided into various sets, e.g., a training set, a validation set, and a test set, at step 110.

[0076] Next, the training data set is used to train the neural network, at step 112. Preferably the neural network is trained using the known Levenberg-Marquardt technique with early stopping. Ordinary back-propagation could be used to train the network, but might take a prohibitively long period of time to converge. Preferably the validation data set is used to determine validation error (mean sum of squared errors), which is used to determine when to stop training the neural network so that the neural network properly generalizes and does not fit noise. More preferably, the neural network is trained until the validation error increases for a specific number of iterations, preferably 5 iterations. The weights from the training iteration immediately before the validation error began increasing (6 iterations back) are used as the final weights. In the alternative, the neural network is trained until the mean sum of squared errors for the training data set is equal to or less than 0.0001.

[0077] Finally, the weights are tested using the test data set, at task 116, by applying the test data set to the trained

neural network and calculating the mean sum of squared errors. If the mean sum of squared errors is relatively low, preferably on the order of about 0.0018, more preferably lower than 0.0018, then the weights have passed this last test. If the mean sum of squared errors is relatively high, i.e., significantly higher than 0.0018, then an alternative neural network structure should be used, e.g., more or fewer hidden neurons, perhaps an additional hidden layer, etc.

[0078] Additionally, the neural network weights can be verified and tested using SWT raw data and force and torque data collected from a vehicle having at least one instrumented hub, e.g., Model 242 electronics and Model 6613 wheel sensor, both from GSE, Inc.

[0079] It is currently believed that because each type of tire (e.g., a Conti Sport Contact, P245/40 R18 as compared to an Ameri★G4S P205/70 R15 as compared to an Contitrac AW P275/65 R17) has different static and dynamic characteristics, each type of tire will require separate data collection and training. Additionally, specific variations in specific tires of the same type might have different enough characteristics to warrant individualized parameters being used by the force prediction unit 22. Accordingly, the processor in the force prediction unit 22 will need to have some means for using the proper neural network weights with the particular type of magnetic tire 30 on the vehicle 10 or specific tire on the vehicle 10. For example, the force prediction unit 22 might have a plurality of pre-loaded weights, number of layers, number of hidden nodes, etc. for a plurality of different types of tires, in which case the force prediction unit 22 need only be apprised of the particular type of tire 30 mounted on the vehicle 10. The force prediction unit 22 can be apprised of the particular type of tire 30 mounted on the vehicle 10 by a number of means, e.g., having one of the SWT sensors read a magnetic code (e.g., a preselected series of magnetic transitions in the form of a bar code or the like embedded into the tire sidewall) directly from the tire sidewall, communicating with an external device 120 (FIG. 2) such as a selectably connectable computer or interface pendant through which the tire type is selected, etc. so that the force prediction unit 22 can associate the proper weights, number of layers, number of hidden nodes, etc. with the tire mounted on the vehicle. In addition, or in the alternative, the force prediction unit 22 can have communication circuitry to directly or indirectly receive neural network parameters such as weights, number of layers, number of hidden nodes, etc. from an external device 120 (FIG. 2) such as a selectably connectable computer or an interface pendant.

[0080] In addition, the neural network is preferably dynamically trained to optimize its weights in real-time. To optimize in real time, the presence of valid training data must be determined. Valid SWT sensor data could be determined using various sensors on the vehicle. For example, ESP systems typically have lateral force accelerometers, which could be used to measure lateral force data correlated with collected SWT sensor data. Additionally, engine torque sensors and other sensors could be used to measure circumferential torque correlated with collected SWT sensor data. Such validated data could be used to retrain the neural network to optimize or otherwise alter the neural network weights.

[0081] Referring now to FIG. 11, and also back to FIG. 2, once the neural network is trained and the force prediction

unit 22 has loaded and/or associated the weights, number of layers, number of hidden nodes, etc. with the mounted tire 30, the force prediction unit 22 predicts forces acting on the tire 30 as generally set forth in routine 200.

[0082] After system initialization, as known to those in the art, data must be collected, at step 202. The raw SWT sensor data is collected in a real-time manner. The raw sensor data is collected, for example, at a rate of at least 100,000 samples per second and input to the processor (e.g., a DSP) in the force prediction unit 22. In the alternative, and preferably, the raw sensor data is collected by analog circuitry that determines mean-crossings (for phase) and peak amplitudes, which are sent to the processor (e.g., a DSP) in the force prediction unit, e.g., by a CAN protocol communications link to be input into the neural network.

[0083] Next, at step 204, the raw SWT sensor data is processed to calculate the inputs to the neural network. In the preferred embodiment, the phase and two amplitudes are calculated from the peaks and zero-crossings of the raw SWT sensor data using analog circuitry. For example, the analog circuitry can determine the phase difference with a phase-locked loop (PLL). The analog circuitry can determine the amplitude of the signal from both SWT sensors 26, 28 by integrating each signal, holding at peak values, and returning the peak values. These phase and both peaks are sent to the processor in the force prediction unit, e.g., by a CAN protocol communications link. The processor determines the difference between the two SWT signal amplitudes by subtracting one peak from the other.

[0084] Having calculated the phase and two amplitudes, next these inputs are corrected at step 206 using various correction methods. Preferably, the phase data is corrected using the additive correction algorithm discussed above. Preferably, both amplitudes are corrected using the multiplicative error correction algorithm discussed above.

[0085] Next, at step 208, the phase data and two amplitudes are normalized, i.e., scaled to between -1 and +1 by ordinary techniques known to those in the art, using the same normalization parameters used to normalize the data at step 108 of FIG. 10.

[0086] Finally, the force prediction unit 22 determines the predicted forces using the scaled, corrected data. In general, the force prediction unit 22 determines any combination or permutation of one or more of any of the following: the lateral force acting on the tire, the circumferential torque acting on the tire, the longitudinal force acting on the tire, the vertical force acting on the tire, and forces and/or torques having any one or more of the foregoing as components thereof. These determined forces and torques are referred to herein as "predicted." Preferably, the force prediction unit 22 determines the predicted circumferential torque on the tire. Preferably, the force prediction unit 22 determines the predicted lateral force acting on the tire. Even more preferably, the force prediction unit 22 determines the predicted lateral force acting on the tire and the predicted circumferential torque acting on the tire.

[0087] Finally, at task 212, the control unit 32 alters the dynamic state of the vehicle 20 via actuators 34 responsive to the force(s) and/or torque(s) predicted by the force prediction unit 22. In addition, or in the alternative, the control unit can produce a qualitative or quantitative display

of any desired parameter on a display unit (not shown). Qualitative displays can be made by comparing predicted forces and/or torques to baseline or threshold forces and/or torques and displaying an appropriate display based on the results of the comparison. Quantitative displays can be numeric displays of predicted force(s) and/or torque(s), and/or values derived therefrom.

[0088] In a second embodiment of the force prediction unit 22 of the present invention, the processor of the force prediction unit 22 implements a bilinear equation in software or in hardware. Preferably there are two bilinear equations--one for lateral force and one for circumferential torque. However, the force prediction unit 22 can be configured to determine any combination or permutation of one or more of any of the following using one bilinear equation for each predicted force or torque: the lateral force acting on the tire, the circumferential torque acting on the tire, the longitudinal force acting on the tire, the vertical force acting on the tire, and forces and/or torques having any one or more of the foregoing as components thereof. Preferably, the magnitude (amplitude) of the outer SWT sensor 26 and the phase difference between the signals of the two SWT sensors 26, 28 are used in each bilinear equation. Even more preferably, the difference in magnitude (amplitude) between the signal from the outer SWT sensor 26 and the signal from the inner SWT sensor 28 is used as an additional variable in each bilinear equation. Thus, the bilinear equations are preferably of the form:

$$M_y = k_1 + k_2 p + k_3 a + k_4 d + k_5 p a$$

$$F_y = k_6 + k_7 p + k_8 a + k_9 d + k_{10} p a$$

[0089] Where,

[0090] p =SWT Phase at 180 degree position, in radians

[0091] a =SWT Amplitude of outer sensor 26 at 180 degree position, in mm

[0092] d =Difference between SWT outer and inner amplitudes, in mm

[0093] M_y =Circumferential torque, kN-m

[0094] F_y =Lateral force, kN

[0095] k_1 - k_{10} =constants from bilinear fit

[0096] The constants k_1 - k_{10} are determined using standard multiple linear regression techniques, which are known to those in the art. More specifically, the bilinear equations are determined as follows. First, steps 102 through 108 are performed as discussed in the text accompanying steps 102-108, resulting in a set of corrected, normalized data. Then the constants k_1 - k_{10} are calculated in MATLAB by regressing Y on X as follows:

$$X = [\text{ones}(n, 1) \ X];$$

$$XTXI = \text{inv}(X' * X);$$

$$COEF = XTXI * X' * Y;$$

[0097] where:

[0098] n is the number of samples

[0099] X is a matrix containing all the phase data, amplitude data, delta data, and phase * amplitude data

[0100] Y is the vector of predicted forces/torques

[0101] Using the bilinear equation embodiment of the force prediction unit of the present invention is identical to the flowchart of FIG. 11, except at step 210, the force(s) and/or torque(s) are predicted using the bilinear equations rather than using a neural network.

[0102] Although the bilinear equations do not appear to perform as well as the trained neural network (see examples below), the predictions from the bilinear equations might well suffice under certain circumstances.

[0103] In addition to the forces and torques described above, the present invention can be applied to derive or determine various calculated values that are useful for vehicle control systems. For example, coefficients of friction can be calculated from F_x , F_y , and F_z determined by the present invention (e.g., by using F_z/F_y and F_z/F_x). As another example, yaw rate for the vehicle can be determined by solving the appropriate vehicle dynamics equations that involve integrating the predicted force equations to, calculate the appropriate angular rate or angular velocity associated with the yaw moments, determined by the present invention.

EXAMPLE 1

[0104] Neural Network

[0105] First, a Conti Sport Contact, 245/40 R18 magnetic sidewall tire was prepared as generally described in U.S. Pat. No. 5,895,854 and copending U.S. patent application Ser. No. 09/347,757, with 200 phr (parts per hundred) of strontium ferrite powder embedded in the sidewall prior to curing. The embedded strontium ferrite was magnetized to magnetic saturation using 96 electromagnets providing 48 North poles alternating with 48 South poles.

[0106] Next, the Conti Sport Contact tire was mounted on an MTS Model 860 tread wear machine (available from MTS Systems Corporation) as follows: The magnetic sidewall tire was mounted to a precision rim. Two pairs of SWT sensors (Philips KMZ10A magneto-resistive sensors) were mounted to a strut fixed to the MTS machine, with one outer and inner pair at 180° and one outer and inner pair at 90°, with each sensor pair using the bracket shown in FIGS. 4 and 5 positioned approximately 12.5 mm from the surface of the sidewall with the tire at rest.

[0107] With the Conti Sport Contact tire mounted in the MTS Model 860 tread wear machine, lateral force, F_y and Torque, M_y , were varied sinusoidally as shown in FIG. 12, with the lateral force being varied sinusoidally at 0.1667 Hz and the torque being varied sinusoidally at 0.100 Hz. The tire was rotated at a fixed, simulated speed of 50 miles per hour.

[0108] Under these circumstances, 30 seconds (750,000 samples) of data, i.e., the circumferential torque, the lateral force, and the vertical force acting on the tire, the inflation pressure, and the raw SWT sensor data, were collected at 25,000 samples per second.

[0109] Next, the raw SWT sensor data was processed to calculate the inputs to the neural network, i.e., the phase difference between the two sensor signals in radians, the amplitude of the signal from the outer sensor 26 in millimeters, and the difference in amplitude between the two sensors 26, 28 in millimeters were calculated from the peaks

and zero-crossings of the raw SWT sensor data. More specifically, the phase difference was determined using the polynomial fit method described above, the amplitude of the signal from the outer SWT sensor 26 was determined using the peak of the polynomial fit described above, and the difference between the two SWT signal amplitudes was determined using the difference between peaks found using the polynomial fit described above.

[0110] Having calculated the phase and two amplitudes, next these input were corrected using the additive correction algorithm described above and both amplitudes were corrected using the multiplicative error correction algorithm described above.

[0111] Next, the phase data and two amplitudes were normalized, i.e., scaled to between -1 and +1 by subtracting the maximum value from the minimum value for each parameter, and dividing by the minimum value, and multiplying the resulting value by each data set.

[0112] Then the large data set was divided into three sets, i.e., a training set, a validation set, and a test set.

[0113] Next, a specific structure was selected for the neural network. For this particular example, a single hidden layer having nine hidden nodes was used, as shown in FIG. 13. A hyperbolic tangent sigmoidal function was used between the inputs and hidden layer. A linear function was used between the hidden layer and outputs. The "180" in the three inputs (Phase 180, Amp 180 Out, and Amp Delta 180) in FIG. 13 refer to the fact that the sensors 26, 28 were mounted at, and thus the data was collected from, the "12 o'clock" position of the tire, i.e., the top of the tire sidewall as viewed on the vehicle. The 90° data could be used to determine the vertical force, F_z .

[0114] Next, the training data set was used to train the neural network with Matlab using the following Matlab neural network object:

[0115] Neural Network Object:

architecture:

```
numInputs: 1
numLayers: 2
biasConnect: [1; 1]
inputConnect: [1; 0]
layerConnect: [0 0; 1 0]
outputConnect: [0 1]
targetConnect: [0 1]
numOutputs: 1 (read-only)
numTargets: 1 (read-only)
numInputDelays: 0 (read-only)
numLayerDelays: 0 (read-only)
```

subobject structures:

```
inputs: {1x1 cell} of inputs
layers: {2x1 cell} of layers
outputs: {1x2 cell} containing 1 output
targets: {1x2 cell} containing 1 target
biases: {2x1 cell} containing 2 biases
inputWeights: {2x1 cell} containing 1 input weight
layerWeights: {2x2 cell} containing 1 layer weight
functions:
```

```
adaptFcn: 'adaptwb'
initFcn: 'initlay'
```

-continued	
performFcn: 'mse'	
trainFcn: 'trainlm'	
parameters:	
adaptParam: .passes	
initParam: (none)	
performParam: (none)	
trainParam: .epochs, .goal, .max_fail, .mem_reduc,	
.min_grad, .mu, .mu_dec, .mu_inc,	
.mu_max, .show, .time	
weight and bias values:	
IW: {2×1 cell} containing 1 input weight matrix	
LW: {2×2 cell} containing 1 layer weight matrix	
b: {2×1 cell} containing 2 bias vectors	
other:	
userdata: (user stuff)	

[0116] The neural network was trained with Matlab using the Levenberg-Marquardt technique with early stopping. More specifically, the neural network was trained until a validation stop (validation set error increased for five consecutive epochs) occurred at epoch **104**. The mean sum of squared errors for the training set at epoch **99** was 0.00176. The mean sum of squared errors for the validation set at epoch **99** was 0.00178.

[0117] Using this procedure, the following weights between the inputs and the hidden layer were determined:

	Phase180	Amp180Out	AmpDelta180
H1	7.5750	-0.3542	0.1623
H2	5.1831	-7.7037	-0.7410
H3	-2.4434	5.5960	0.8778
H4	-0.1242	0.9222	-1.3954
H5	5.4329	-7.8189	-1.0483
H6	-0.1375	0.6883	-0.3193
H7	5.6597	3.0346	-0.9307
H8	0.8117	1.3816	-0.5938
H9	1.0578	-1.2053	1.1388

[0118] Additionally, the following weights between the hidden layer and the outputs were determined:

	H1	H2	H3	H4	H5	H6	H7	H8	H9
M _y	-0.2718	0.2565	-0.0748	0.2405	-0.2624	-1.2731	0.2896	0.6869	0.7063
F _y	0.5201	-1.3359	0.0085	-1.0817	1.3245	4.5544	-0.1567	-0.1339	0.1094

[0119] The following bias weights between the inputs and the hidden layer were determined:

H1	-7.8421
H2	-0.9515
H3	1.5128
H4	-0.1678
H5	-0.9816
H6	-0.7893

-continued	
H7	-4.8751
H8	0.3697
H9	0.5579

[0120] Finally, the following bias weights between the hidden layer and the outputs were determined:

M _y	-1.2825
F _y	3.2547

[0121] These particular weights are considered to be valid because the training set, the validation set and the test set all had a mean sum of squared errors that were below 0.002 (all were about 0.00178).

[0122] **FIGS. 14 and 15** show a graphical representation of the closeness of the predictions as compared to measured data in the validation set. Using these weights, the lateral force predicted by the neural network is very close to the measured lateral force in the validation set. Similarly, the circumferential torque predicted by the neural network is very close to the measured circumferential torque in the validation set

EXAMPLE 2

[0123] Bilinear Equations

[0124] In this example, the data from Example 1 was used to determine a pair of bilinear equations to predict lateral force and circumferential torque.

[0125] The constants for the two equations were calculated with Matlab using the multiple linear least squares regression technique.

[0126] Using the above procedure, the following bilinear equations were determined to predict lateral force and circumferential torque:

$$M_y = -5.9835 + 7.4517p - 0.7741a + 0.3313d + 0.7102pa$$
$$F_y = -39.6433 + 7.7312p + 6.2483a + 9.7848d - 2.8222pa$$

[0127] Where,

[0128] p=SWT Phase at 180 degree position, in radians

[0129] a=SWT Amplitude of outer sensor **26** at 180 degree position, in mm

[0130] d=Difference between SWT outer and inner amplitudes, in mm

[0131] M_y=Circumferential torque, kN-m

[0132] F_y=Lateral Force, kN

[0133] FIGS. 16 and 17 show graphical representations of the closeness of the predictions as compared to measured data in the validation set. Using these bilinear equations, the predicted lateral force is close to the measured lateral force in the validation set. Similarly, the predicted circumferential torque is close to the measured circumferential torque in the validation set. Although the predictions made by the bilinear equations are not as close as the predictions made by the neural network, as can be seen by inspection of FIGS. 14-17, the bilinear equations provide reasonably accurate predictions, which can be useful and usable for various applications. Additionally, the greatest deviation between predicted and measured values appears to be when there is no force or torque being applied.

EXAMPLE 3

[0134] Neural Network

[0135] An Contitrac AW P275/65 R17 magnetic sidewall tire was prepared as generally described in U.S. Pat. No. 5,895,854 and copending U.S. patent application Ser. No. 09/347,757, with 200 phr (parts per hundred) of strontium ferrite powder embedded in the sidewall prior to curing. The embedded strontium ferrite was magnetized to magnetic saturation using 96 electromagnets providing 48 North poles alternating with 48 South poles.

[0136] Next, the Contitrac AW P275/65 R17 tire was mounted on an MTS Model 860 tread wear machine (available from MTS Systems Corporation) as follows: The magnetic sidewall tire was mounted to a precision rim. Two pairs of SWT sensors (Philips KMZ10A magneto-resistive sensors) were mounted to a strut fixed to the MTS machine, with one outer and inner pair at 180° and one outer and inner pair at 90°, with each sensor pair using the bracket shown in FIGS. 4 and 5 positioned approximately 12.5 mm from the surface of the sidewall with the tire at rest.

[0137] With the Contitrac AW P275/65 R17 tire mounted in the MTS Model 860 tread wear machine, vertical force, F_z , lateral force, F_y , and Torque, M_y , were varied sinusoidally similar to Example 1, with the vertical force being varied sinusoidally at 0.25 Hz, the lateral force being varied sinusoidally at 0.15 Hz, and the torque being varied sinusoidally at 0.100 Hz. The tire was rotated at a fixed, simulated speed of 50 miles per hour.

[0138] Under these circumstances, 20 seconds (500,000 samples) of data, i.e., the circumferential torque, the lateral force, and the vertical force acting on the tire, the inflation pressure, and the raw SWT sensor data, were collected at 25,000 samples per second.

[0139] Next, the raw SWT sensor data was processed to calculate the eight inputs to the neural network, i.e., (1) the phase difference between the two 180° sensor signals in radians (Phase180), (2) the amplitude of the signal from the outer 180° sensor in millimeters (Amp180Out or Amp180), (3) the difference in amplitude between the two 180° sensors in millimeters (AmpDelta180 or Delta180), (4) the phase difference between the two 90° sensor signals in radians (Phase90), (5) the amplitude of the signal from the outer 90° sensor in millimeters (Amp90Out or Amp180), (6) the difference in amplitude between the two 90° sensors in millimeters (AmpDelta90 or Delta90), (7) Phase180×Amp180Out (after the correction routine was performed)

(pxA180), and (8) Phase90×Amp90Out (after the correction routine was performed) (pxA90) were calculated from the peaks and zero-crossings of the raw SWT sensor data. More specifically, the phase differences were determined using the polynomial fit method described above, the amplitudes of the signals from the outer SWT sensors were determined using the peaks of the polynomial fit described above, and the differences between the two signal amplitudes were determined using the differences between peaks found using the polynomial fit described above.

[0140] Having calculated the eight phase and two amplitudes, next these inputs were corrected using the additive correction algorithm described above and both amplitudes were corrected using the multiplicative error correction algorithm described above.

[0141] Next, the eight inputs were normalized, i.e., scaled to between -1 and +1 by subtracting the maximum value from the minimum value for each parameter, and dividing by the minimum value, and multiplying the resulting value by each data set.

[0142] Then the large data set was divided into three sets, i.e., a training set, a validation set, and a test set.

[0143] Next, a specific structure was selected for the neural network. For this particular example, a single hidden layer having six hidden nodes was used. A hyperbolic tangent sigmoidal function was used between the inputs and hidden layer. A linear function was used between the hidden layer and outputs.

[0144] Next, the training data set was used to train the neural network with Matlab using the following Matlab neural network object:

```

Neural Network object:
architecture:

    numInputs: 1
    numLayers: 2
    biasConnect: [1; 1]
    inputConnect: [1; 0]
    layerConnect: [0 0; 1 0]
    outputConnect: [0 1]
    targetConnect: [0 1]
    numOutputs: 1 (read-only)
    numTargets: 1 (read-only)
    numInputDelays: 0 (read-only)
    numLayerDelays: 0 (read-only)
    subobject structures:

        inputs: {1×1 cell} of inputs
        layers: {2×1 cell} of layers
        outputs: {1×2 cell} containing 1 output
        targets: {1×2 cell} containing 1 target
        biases: {2×1 cell} containing 2 biases
        inputWeights: {2×1 cell} containing 1 input weight
        layerWeights: {2×2 cell} containing 1 layer weight
        functions:

            adaptFcn: 'adaptwb'
            initFcn: 'initlay'
            performFcn: 'mse'
            trainFcn: 'trainlm'
        parameters:

            adaptParam: .passes
            initParam: (none)
            performParam: (none)

```

-continued	
trainparam:	.epochs, .goal, .max_fail, .mem_reduc, .min_grad, .mu, .mu_dec, .mu_inc, .mu_max, .show, .time
weight and bias values:	
IW:	{2x1 cell} containing 1 input weight matrix
LW:	{2x2 cell} containing 1 layer weight matrix
b:	{2x1 cell} containing 2 bias vectors
other:	
userdata:	(user stuff)

[0145] The neural network was trained with Matlab using the Levenberg-Marquardt technique with early stopping. More specifically, the neural network was trained until a validation stop (validation set error increased for five consecutive epochs) occurred at epoch **81**. The mean sum of squared errors for the training set at epoch **76** was 0.00023. The mean sum of squared errors for the validation set at epoch **76** was 0.0003.

[0146] Using this procedure, the following weights between the inputs and the hidden layer were determined:

	Phase180	Amp180	Delta180	Phase90	Amp90	Delta90	pxA180	pxA90
H1	-3.1924	0.1511	-0.2810	0.0578	-2.4559	1.3095	2.6048	-0.1632
H2	0.2276	0.1292	0.0095	-0.0452	-0.1124	0.1021	-0.5314	0.0715
H3	4.0264	-2.7292	6.4593	-1.7411	-0.9765	0.2611	-4.0561	1.8814
H4	-3.4893	1.6882	-0.4483	-0.5887	-0.6309	-0.4819	3.8759	0.3948
H5	0.1973	0.0347	-0.3096	0.2210	-0.4999	0.5343	-0.4009	-0.0815
H6	-0.3868	-1.3459	1.1311	-0.2410	3.6300	-2.9317	0.7292	0.3695

[0147] Additionally, the following weights between the hidden layer and the outputs were determined:

	H1	H2	H3	H4	H5	H6
M _y	-0.1101	-3.4672	0.0003	0.0521	0.5608	0.9396
F _y	-0.0784	3.3440	0.0104	-0.5603	-3.7565	0.1112
F _z	-4.7038	8.4356	0.3594	1.6993	11.3365	5.3866

[0148] The following bias weights between the inputs and the hidden layer were determined:

H1	1.4653
H2	0.3718
H3	-1.3782
H4	0.5840
H5	0.2758
H6	0.7870

[0149] Finally, the following bias weights between the hidden layer and the outputs were determined:

M _y	0.7171
F _y	-0.0399
F _z	-6.2700

[0150] These particular weights are considered to be valid because the training set, the validation set and the test set all had a mean sum of squared errors that were below 0.002 (all were about 0.0003 or less).

[0151] FIGS. **18-20** show graphical representations of the closeness of the predictions as compared to measured data in the validation set. Using these weights, the vertical force, lateral force, and circumferential torque predicted by the neural network is nearly identical to the measured values in the validation set.

EXAMPLE 4

[0152] Bilinear Equations

[0153] In this example, the data from Example 2 was used to determine bilinear equations to predict vertical force, lateral force, and circumferential torque.

[0154] The constants for the two equations were calculated with Matlab using the multiple linear least squares regression technique.

[0155] Using the above procedure, the following bilinear equations were determined to predict vertical force, lateral force, and circumferential torque:

$$F_y = -12.9336 + -11.9139p180 - 4.4413a180 + 9.9952d180 - 5.7197p90 + 4.1038a90 - 5.5416d90 + 0.1871(p180 \times a180) + 0.0676(p90 \times a90)$$
$$F_z = 8.6908 - 79.1627p180 - 1.1944a180 + 1.4968d180 + 10.8531p90 + 1.2659a90 + 0.0597d190 + 3.5677(p180 \times a180) + 0.7880(p90 \times a90)$$
$$M_y = -0.9059 + 6.5357p180 - 0.6891a180 + 1.6094d180 + 0.0920p90 + 0.4191a90 - 0.6654d90 + 0.3710(p180 \times a180) - 0.0027(p90 \times a90)$$

[0156] Where,

[0157] p180=SWT Phase at 180 degree position, radians

[0158] a180=SWT Amplitude of outer sensor at 180 degree position, mm

[0159] d180=Difference between SWT outer and inner amplitudes at 180 degrees, mm

[0160] p90=SWT Phase at 90 degree position, radians

[0161] a90=SWT Amplitude of outer sensor at 90 degree position, mm

[0162] d_{90} =Difference between SWT outer and inner amplitudes at 90 degrees, mm

[0163] F_y =Lateral force in kN

[0164] F_z =Vertical (Normal) force in kN

[0165] M_y =Circumferential torque, kN-m

[0166] FIGS. 22-24 show graphical representations of the closeness of the predictions as compared to measured data in the validation set. Using these bilinear equations, the predicted vertical force, lateral force, and circumferential torque are very close to the measured values. Although the predictions made by the bilinear equations are not as close as the predictions made by the neural network, with the additional sensor pair, the bilinear equations in this example provide very accurate predictions, which can be useful and usable for many applications.

[0167] An additional example is attached hereto as Appendix 1 and incorporated herein by reference.

[0168] Referring back to FIG. 2, as mentioned above, exemplary control units 32 benefiting from the present invention include but are not limited to ABS control units, traction control system (TCS) control units, electronic stability control (ESC) control units, integrated vehicle dynamics (IVD) control units, locked differential control units, suspension control units, brake assist control units, intelligent cruise control units, steering assist control units, deflation detection control units, navigation control units, roll-over prevention control units, and a brake-by-wire control units.

[0169] ABS control units can benefit from the present invention in at least two ways. First, the present invention can be used to reduce ABS chattering. ABS chattering typically results from the nature of slip data. Force data provided by the present invention is smoother than slip data. Accordingly, an ABS controller using force data taken in accordance with the present invention will have less chattering.

[0170] Also, ABS control units can be made safer using the lateral force predicted by the present invention. Referring now to FIG. 18, a series of μ -slip curves at various steering angles (α) are shown. No steering results in no lateral force. Curve 200 is a typical μ -slip curve showing longitudinal force (i.e., braking force) F_x at a steering angle of 0° , i.e., under no lateral force. As shown by that curve 200 and as known to those in the art, the peak of that curve 200 is at a point 202 at about 13% slip. As also known to those in the art, it is desirable for an ABS control unit to strive to control the slip to provide peak braking force at about 10% slip or so.

[0171] A steering motion causes a tire to rotate, which induces a lateral force on the tire. Curves 210 and 220 in FIG. 18 are μ -slip curves showing longitudinal force F_x at a steering angle of 5° and 10° , respectively. The corresponding lateral forces F_y are also shown. The peak of curve 210 is at a point 212 at about 20% slip and the peak of curve 220 is at a point 222 at about 32% slip. That is, a lateral force on the tire, as caused by a steering maneuver, causes the peak of the μ -slip curve to be moved.

[0172] The effect of this should be apparent. An ABS control unit incapable of detecting lateral force would strive

to control the slip at about 10% slip or so, which would be effective for maximum braking force as long as there is no steering action. However, a slip at around 10% is not at the peak of the curves 210 and 220. Therefore, a steering maneuver would confound the ABS control unit incapable of detecting lateral force, rendering it incapable of generating a maximum braking force.

[0173] On the other hand, an ABS controller 32 modified to accept a predicted lateral force from a force prediction unit 22 of the present invention (or even implemented with the same processor) could vary the slip control point in accordance with the predicted lateral force to provide maximum braking force. For example, the ABS control unit 32 could be modified to select a μ -slip curve or other control parameter based on the predicted lateral force from the force prediction unit 22. In the context of FIG. 18 a first predicted lateral force would be used to trigger curve 210 to be used, and the ABS control unit 32 would tend to control the slip at about point 212 to provide maximum braking. A different, greater predicted lateral force would be used to trigger curve 220 to be used, and the ABS control unit 32 would then tend to control the slip at about point 222 to provide maximum braking. Changing the prediction of lateral force at any instant would change the μ -slip curve used the next instant. Although only three μ -slip curves are described in this example, one of ordinary skill in the art would understand that more curves could be used, or the lateral force (or some other parameter determined by the force prediction unit 22) could be used in an equation or set of equations by the ABS control unit 32 to vary the slip control point in accordance with the predicted lateral force.

[0174] While the present invention has been illustrated by the description of embodiments thereof, and while the embodiments have been described in considerable detail, it is not the intention of the applicant to restrict or in any way limit the scope of the appended claims to such detail. Additional advantages and modifications will readily appear to those skilled in the art. For example, the SWT sensors described herein have an analog current output; in the alternative, sensors having outputs in the frequency domain might be used in a system made in accordance with the teachings of the present invention. In addition, the SWT sensors described herein are magnetic sensors; other side-wall torsion sensors might be used in a system made in accordance with the teachings of the present invention. Therefore, the invention in its broader aspects is not limited to the specific details, representative apparatus and method, and illustrative examples shown and described. Accordingly, departures may be made from such details without departing from the spirit or scope of the applicant's general inventive concept.

I claim:

1. A vehicle control system, comprising: a force prediction unit for being placed in circuit communication with a tire deformation sensor and at least one other sensor, receiving a tire deformation input from the tire deformation sensor, and receiving at least one other tire sensor input from the at least one other sensor, said force prediction unit comprising a preprogrammed processor receiving the tire deformation input and the at least one other sensor input, said force prediction unit characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire

deformation input and the at least one other sensor input an output corresponding to a predicted circumferential torque or longitudinal force acting on a tire.

2. The vehicle control system of claim 1, wherein said preprogrammed processor of said force prediction unit executes code implementing a neural network trained with previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire.

3. The vehicle control system of claim 1, wherein said preprogrammed processor of said force prediction unit executes code implementing a multi-layer neural network trained with previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire, said multi-layer neural network having an input layer, at least one hidden layer, and an output layer.

4. The vehicle control system of claim 3, wherein said preprogrammed processor implements equations between said input layer and said at least one hidden layer in the form of a hyperbolic tangent sigmoidal transfer function, and wherein said preprogrammed processor implements equations between said hidden layer and said output layer in the form of a linear function.

5. The vehicle control system of claim 1, wherein said preprogrammed processor of said force prediction unit executes code implementing an equation using constants determined using multiple-linear-least squares regression analysis of previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire.

6. The vehicle control system of claim 5, wherein the equation implemented by the preprogrammed processor of said force prediction unit is a bilinear equation.

7. The vehicle control system of claim 1, wherein said the tire deformation input and the at least one other sensor input comprise (a) a phase input related to a phase difference between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said preprogrammed processor accepting as inputs the phase input and the amplitude input and using at least the phase input and amplitude input to determine at least an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire.

8. The vehicle control system of claim 2, wherein said the tire deformation input and the at least one other sensor input comprise (a) a phase input related to a phase difference between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said neural network accepting as inputs the phase input and the amplitude input and using at least the phase input and amplitude input to determine at least an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire.

9. The vehicle control system of claim 6, wherein said the tire deformation input and the at least one other sensor input comprise (a) a phase input related to a phase difference

between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said bilinear equation being a function of at least the phase input and the amplitude input to determine an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire.

10. The vehicle control system of any of claims 1-9, wherein the tire deformation sensor comprises a magnetic tire sidewall torsion (SWT) sensor, said SWT sensor including a magnetic sensor positioned proximate to a sidewall of the tire that has been magnetized with alternating magnetic poles.

11. A vehicle control system, comprising: a force prediction unit for being placed in circuit communication with a tire deformation sensor and at least one other sensor, receiving a tire deformation input from the tire deformation sensor, and receiving at least one other tire sensor input from the at least one other sensor, said force prediction unit comprising a preprogrammed processor receiving the tire deformation input and the at least one other sensor input, said force prediction unit characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted lateral force acting on a tire.

12. The vehicle control system of claim 11, wherein said preprogrammed processor of said force prediction unit executes code implementing a neural network trained with previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted lateral force acting on the tire.

13. The vehicle control system of claim 11, wherein said preprogrammed processor of said force prediction unit executes code implementing a multi-layer neural network trained with previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted lateral force acting on the tire, said multi-layer neural network having an input layer, at least one hidden layer, and an output layer.

14. The vehicle control system of claim 13, wherein said preprogrammed processor implements equations between said input layer and said at least one hidden layer in the form of a hyperbolic tangent sigmoidal transfer function, and wherein said preprogrammed processor implements equations between said hidden layer and said output layer in the form of a linear function.

15. The vehicle control system of claim 11, wherein said preprogrammed processor of said force prediction unit executes code implementing an equation using constants determined using multiple-linear-least squares regression analysis of previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted lateral force acting on the tire.

16. The vehicle control system of claim 15, wherein the equation implemented by the preprogrammed processor of said force prediction unit is a bilinear equation.

17. The vehicle control system of claim 11, wherein said the tire deformation input and the at least one other sensor

input comprise (a) a phase input related to a phase difference between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said preprogrammed processor accepting as inputs the phase input and the amplitude input and using at least the phase input and amplitude input to determine at least an output corresponding to a predicted lateral force acting on the tire.

18. The vehicle control system of claim 12, wherein said the tire deformation input and the at least one other sensor input comprise (a) a phase input related to a phase difference between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said neural network accepting as inputs the phase input and the amplitude input and using at least the phase input and amplitude input to determine at least an output corresponding to a predicted lateral force acting on the tire.

19. The vehicle control system of claim 16, wherein said the tire deformation input and the at least one other sensor input comprise (a) a phase input related to a phase difference between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said bilinear equation being a function of at least the phase input and the amplitude input to determine an output corresponding to a predicted lateral force acting on the tire.

20. The vehicle control system of any of claims **11-19**, wherein the tire deformation sensor comprises a magnetic tire sidewall torsion (SWT) sensor, said SWT sensor including a magnetic sensor positioned proximate to a sidewall of the tire that has been magnetized with alternating magnetic poles.

21. A vehicle control system, comprising: a force prediction unit for being placed in circuit communication with a tire deformation sensor and at least one other sensor, receiving a tire deformation input from the tire deformation sensor, and receiving at least one other tire sensor input from the at least one other sensor, said force prediction unit comprising a preprogrammed processor receiving the tire deformation input and the at least one other sensor input, said force prediction unit characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted vertical force acting on a tire.

22. The vehicle control system of claim 21, wherein said preprogrammed processor of said force prediction unit executes code implementing a neural network trained with previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted vertical force acting on the tire.

23. The vehicle control system of claim 21, wherein said preprogrammed processor of said force prediction unit executes code implementing a multi-layer neural network trained with previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted vertical

force acting on the tire, said multi-layer neural network having an input layer, at least one hidden layer, and an output layer.

24. The vehicle control system of claim 23, wherein said preprogrammed processor implements equations between said input layer and said at least one hidden layer in the form of a hyperbolic tangent sigmoidal transfer function, and wherein said preprogrammed processor implements equations between said hidden layer and said output layer in the form of a linear function.

25. The vehicle control system of claim 21, wherein said preprogrammed processor of said force prediction unit executes code implementing an equation using constants determined using multiple-linear-least squares regression analysis of previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted vertical force acting on the tire.

26. The vehicle control system of claim 25, wherein the equation implemented by the preprogrammed processor of said force prediction unit is a bilinear equation.

27. The vehicle control system of claim 21, wherein said the tire deformation input and the at least one other sensor input comprise (a) a phase input related to a phase difference between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said preprogrammed processor accepting as inputs the phase input and the amplitude input and using at least the phase input and amplitude input to determine at least an output corresponding to a predicted vertical force acting on the tire.

28. The vehicle control system of claim 22, wherein said the tire deformation input and the at least one other sensor input comprise (a) a phase input related to a phase difference between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said neural network accepting as inputs the phase input and the amplitude input and using at least the phase input and amplitude input to determine at least an output corresponding to a predicted vertical force acting on the tire.

29. The vehicle control system of claim 26, wherein said the tire deformation input and the at least one other sensor input comprise (a) a phase input related to a phase difference between the at least two sensors and indicative of torsional deformation of the tire and (b) an amplitude input related to a distance between the tire sidewall and the tire deformation sensor and indicative of a force acting on the tire, said bilinear equation being a function of at least the phase input and the amplitude input to determine an output corresponding to a predicted vertical force acting on the tire.

30. The vehicle control system of any of claims **21-29**, wherein the tire deformation sensor comprises a magnetic tire sidewall torsion (SWT) sensor, said SWT sensor including a magnetic sensor positioned proximate to a sidewall of the tire that has been magnetized with alternating magnetic poles.

31. The vehicle control system of claim 1, wherein said force prediction unit is further characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input

(a) an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire and (b) an output corresponding to a predicted force acting on the tire that is skewed with respect to the longitudinal force acting on the tire.

32. The vehicle control system of claim 31, wherein said force prediction unit is further characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input (a) an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire and (b) an output corresponding to a predicted lateral force acting on the tire.

33. The vehicle control system of claim 31, wherein said force prediction unit is further characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input (a) an output corresponding to a predicted circumferential torque or longitudinal force acting on the tire and (b) an output corresponding to a predicted vertical force acting on the tire.

34. The vehicle control system of claim 10, wherein said force prediction unit is further characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input (a) an output corresponding to a predicted lateral force acting on the tire and (b) an output corresponding to a predicted force acting on the tire that is skewed with respect to the lateral force acting on the tire.

35. The vehicle control system of claim 34, wherein said force prediction unit is further characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input (a) an output corresponding to a predicted lateral force acting on the tire and (b) an output corresponding to a predicted vertical force acting on the tire.

36. The vehicle control system of claim 20, wherein said force prediction unit is further characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input (a) an output corresponding to a predicted vertical force acting on the tire and (b) an output corresponding to a predicted force acting on the tire that is skewed with respect to the vertical force acting on the tire.

37. A vehicle control system comprising:

- (a) a force prediction unit for being placed in circuit communication with a tire deformation sensor and at least one other sensor, receiving a tire deformation input from the tire deformation sensor, and receiving at least one other tire sensor input from the at least one other sensor, said force prediction unit comprising a preprogrammed processor receiving the tire deformation input and the at least one other sensor input, said force prediction unit characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted circumferential torque or longitudinal force act-

ing on a tire and outputting a predicted circumferential torque or longitudinal force output corresponding to the predicted circumferential torque or longitudinal force acting on the tire; and

- (b) a control unit in circuit communication with said force prediction unit for receiving the predicted circumferential torque or longitudinal force output and for being placed in circuit communication with vehicle actuators, said control unit characterized by altering the dynamic state of the vehicle via the actuators responsive at least in part to the predicted circumferential torque or longitudinal force output from the force prediction unit.

38. A vehicle control system comprising:

- (a) a force prediction unit for being placed in circuit communication with a tire deformation sensor and at least one other sensor, receiving a tire deformation input from the tire deformation sensor, and receiving at least one other tire sensor input from the at least one other sensor, said force prediction unit comprising a preprogrammed processor receiving the tire deformation input and the at least one other sensor input, said force prediction unit characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted lateral force acting on a tire and outputting a predicted lateral force output corresponding to the predicted lateral force acting on the tire; and
- (b) a control unit in circuit communication with said force prediction unit for receiving the predicted lateral force output and for being placed in circuit communication with vehicle actuators, said control unit characterized by altering the dynamic state of the vehicle via the actuators responsive at least in part to the predicted lateral force output from the force prediction unit.

39. The vehicle control system of claim 38, wherein said control unit has associated therewith a plurality of μ -slip curves, each of said μ -slip curves being associated with a different lateral force, said control unit implementing an anti-lock braking system based on a selected one of said μ -slip curves, and further wherein said control unit is characterized by selecting the of said plurality of μ -slip curves responsive at least in part to the predicted lateral force output from the force prediction unit and using the selected one of said plurality of μ -slip curves to implement anti-lock braking.

40. A vehicle control system comprising:

- (a) a force prediction unit for being placed in circuit communication with a tire deformation sensor and at least one other sensor, receiving a tire deformation input from the tire deformation sensor, and receiving at least one other tire sensor input from the at least one other sensor, said force prediction unit comprising a preprogrammed processor receiving the tire deformation input and the at least one other sensor input, said force prediction unit characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted vertical force acting on a tire and outputting a

predicted vertical force output corresponding to the predicted vertical force acting on the tire; and

- (b) a control unit in circuit communication with said force prediction unit for receiving the predicted vertical force output and for being placed in circuit communication with vehicle actuators, said control unit characterized by altering the dynamic state of the vehicle via the actuators responsive at least in part to the predicted vertical force output from the force prediction unit.

41. A method of predicting the circumferential torque or longitudinal force acting on a tire, comprising the steps of:

- (a) providing a force prediction unit for being placed in circuit communication with a tire deformation sensor and at least one other sensor, receiving a tire deformation input from the tire deformation sensor, and receiving at least one other tire sensor input from the at least one other sensor, said force prediction unit comprising a preprogrammed processor receiving the tire deformation input and the at least one other sensor input, said force prediction unit characterized by implementing preprogrammed equations having constants determined from previously collected data to determine from at least the tire deformation input and the at least one other sensor input an output corresponding to a predicted vertical force acting on a tire;

- (b) collecting tire deformation input from the tire deformation sensor and the at least one other tire sensor input from the at least one other sensor; and

- (c) determining with the force prediction unit the circumferential torque or longitudinal force acting on a tire from the collected tire deformation input and the collected at least one other tire sensor input.

42. A method of training a neural network to determine the circumferential torque or longitudinal force acting on a tire from a tire deformation sensor and at least one other sensor, comprising the steps of:

- (a) collecting tire deformation input from a tire deformation sensor and at least one other tire sensor input from at least one other sensor;
- (b) collecting an input corresponding to the circumferential torque or longitudinal force acting on the tire;
- (c) training the neural network to predict the circumferential torque or longitudinal force acting on a tire using as training data at least the collected tire deformation input, the collected at least one other tire sensor input, and the collected input corresponding to the circumferential torque or longitudinal force acting on the tire.

* * * * *